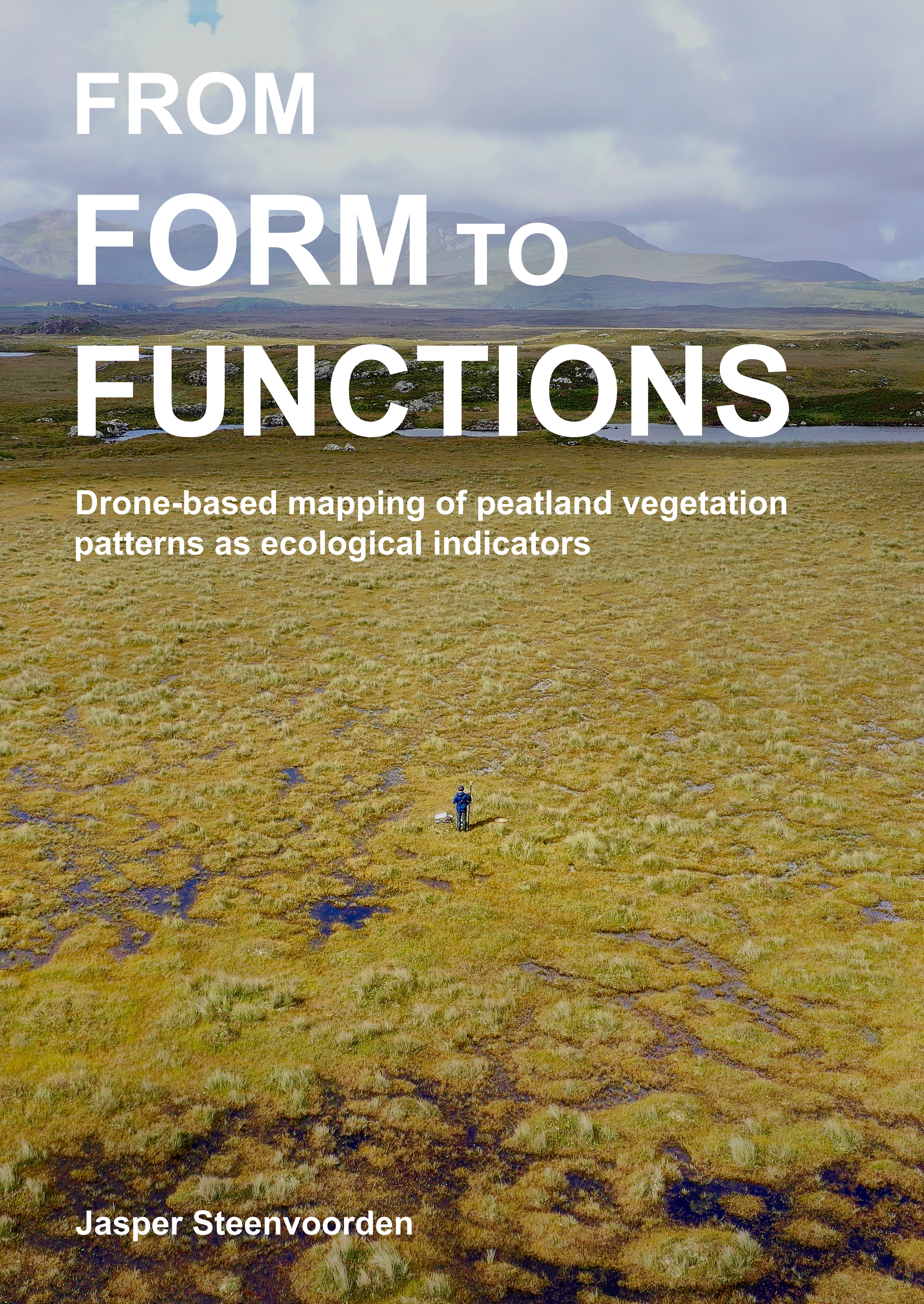

FROM FORM TO FUNCTIONS

Drone-based mapping of peatland vegetation patterns as ecological indicators

Jasper Steenvoorden

Propositions

1. The commonly used definition of biodiversity is unsuitable for peatlands (this thesis).
2. Peatland restoration projects are valued too much on carbon storage at the expense of other important services (this thesis).
3. Cultivating a sense of connection with the ecosystem(s) you work in ensures more careful and sustainable research practices.
4. The value of citizen science projects is severely underestimated.
5. The current democratic system in the Netherlands is inadequate to tackle national environmental challenges.
6. Spending more time in wilderness will lead to a more fulfilled life.

Propositions belonging to the thesis, entitled

From form to functions: Drone-based mapping of peatland vegetation patterns as ecological indicators

Jasper Steenvoorden,
Wageningen, 11 October 2024

From form to functions

Drone-based mapping of
peatland vegetation patterns
as ecological indicators

Jasper Steenvoorden

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This research was conducted under the auspices of the Graduate School for Socio-Economic and Natural Sciences of the Environment (SENSE)

From form to functions

Drone-based mapping of peatland vegetation patterns as ecological indicators

Jasper Steenvoorden

Thesis

Submitted in fulfilment of the requirements for the degree of doctor

at Wageningen University

by the authority of Rector Magnificus

Prof. Dr. Carolien Kroeze,

in the presence of the

Thesis Committee approved by the Academic Board

on Friday 11 October 2024

at 15:30 in the Omnia Auditorium.

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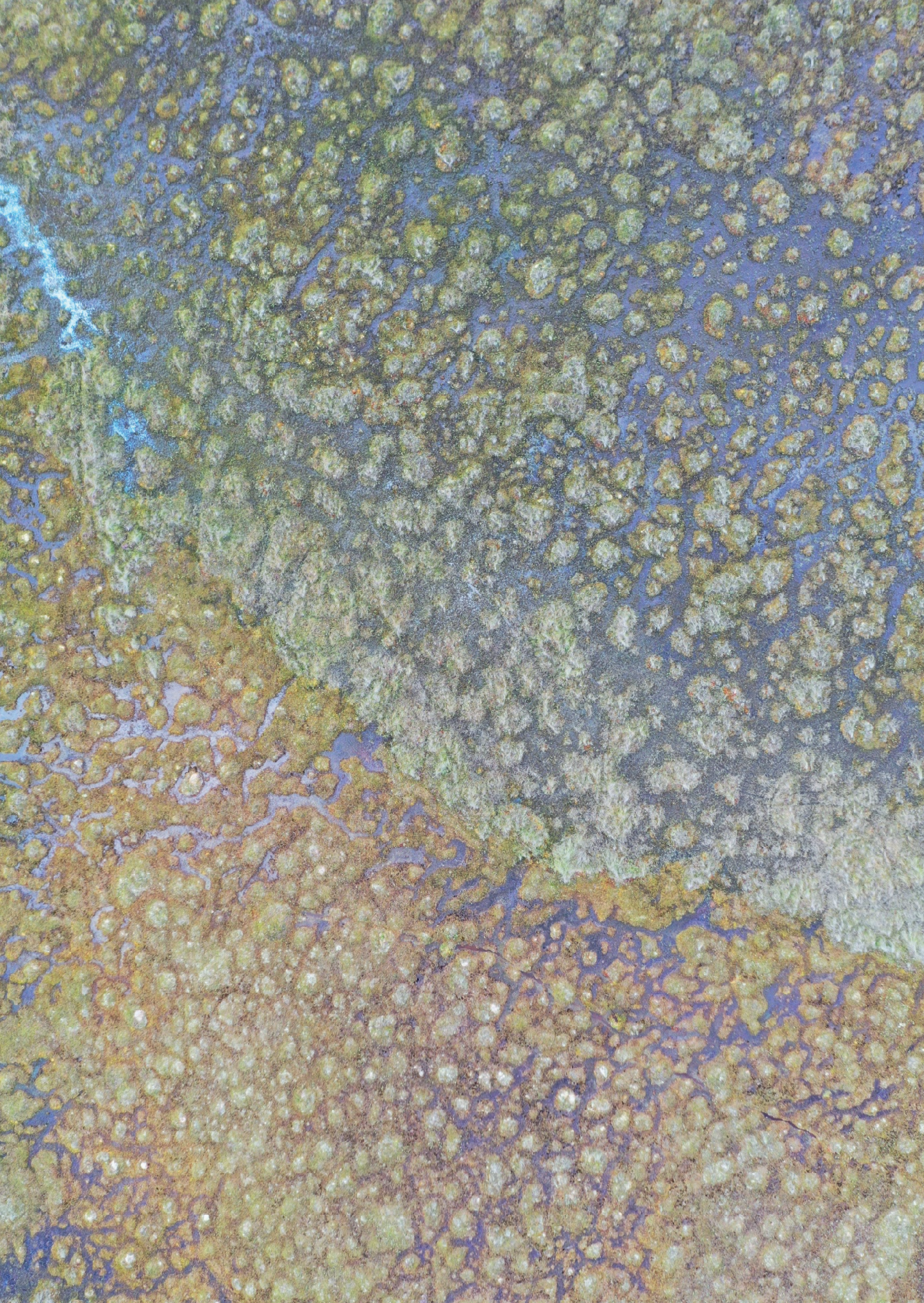


Chapter 1

General introduction

1.1 Northern peatlands

1.1.1 Defining northern peatlands

This thesis deals with the beautiful and fascinating world of peatlands. Peatlands can be defined as terrestrial wetland ecosystems where waterlogged conditions prevent plant material from fully decomposing, leading to accumulation of deposits rich in incompletely decomposed organic matter also called peat. Peatlands occur widespread across the globe and range from tropical peat forests and wooded swamps to fens, blanket bogs and raised bogs. The variation in terminology we use to describe peatlands reflects their complexity and diversity. Globally, peatlands encompass around 4.2 million km^2, which represents about 3% of the total land area (Melton et al., 2022; Xu et al., 2018). Yet, the largest part of peatland area can be found in temperate and boreal climates in the northern hemisphere above 45ºN, constituting about 68% of their total coverage (Figure 1.1). These peatlands are referred to as northern peatlands and are the focal region of this thesis.

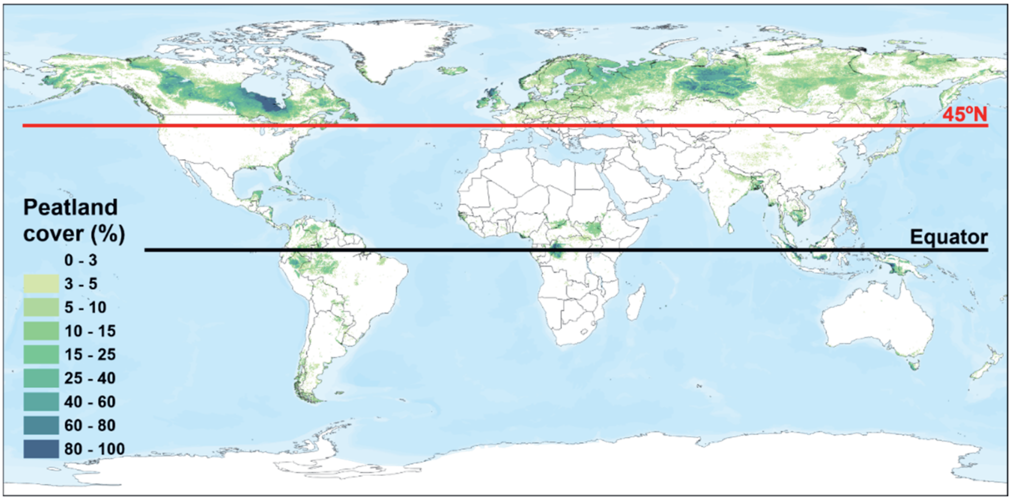


Figure 1.1 Global distribution and cover of peatlands at five arcmin spatial resolution (ca. 9.26km at the equator and 4.63km at 60ºN) as estimated by Peat-ML; Melton et al., 2022). Peatland cover between 0–3% was labelled transparent. The 45ºN line generally indicates the lowest latitude cut-off point for defining northern peatlands.

1.1.2 Peatland formation and development

The formation and development of most northern peatlands, which I refer to as peatlands from now on, started after the last Ice Age about 10.000–5000 years ago following the retreat and melting of the Pleistocene glaciers. As a result, shallow waters emerged in the form of ponds, lakes or slow-flowing rivers. In these water bodies, peat accumulated continuously through the decay of vegetation growing at its margins and occurring at rates of about 1–2mm/year (Rydin & Jeglum, 2013). Initial peat formation also occurred on very wet mineral soils because of water table rise and associated moderation in climate (Wieder et al., 2006). Peatlands in this early development still contained relatively neutral or alkaline pH levels and higher nutrient levels because they were predominantly fed by surface- and ground-waters. This resulted in vegetation types more indicative of such environmental conditions. A peatland at this developmental stage is also called a fen. However, the distance between the peat surface and mineral soils or groundwater increased over time due to the gradual accumulation of peat. Because peat has a relatively low permeability, the relative influence of rainwater in the rooting zone also increased, consequently making its water quality more acid and nutrient-poor. These environmental changes invariably caused succession towards plant species that are adapted to such conditions, and peatlands at this developmental stage are called a bog. The long-term trend from fen to bog through acidification and decreasing nutrient-availability is called ombrotrophication and is typically regarded as the final stage of peatland development (Rydin & Jeglum, 2013).

1.1.3 Bog types and their main characteristics

While the term ‘bog’ already specifies peatlands that are characterised by waterlogged, highly acidic and nutrient-poor surface conditions, bogs can generally be subdivided further into raised and blanket bogs. Most of the peatlands that were studied in this thesis are raised bogs, while some are blanket bogs. All of them occur in Ireland (see also section 1.7). I will therefore use the broader term peatlands to refer to both bog types simultaneously from now on, unless specified otherwise. While both peatland types are similar, there are important differences in the distribution, development, structure, and vegetation of raised and blanket bogs which are predominantly driven by gradients in temperature, precipitation, elevation, and topography (Schouten, 1984). Raised bogs (Figure 1.2A) develop in relatively isolated positions in the landscape, and fill up poorly drained depressions. Besides, they typically have a gently domed surface from centre to margin due to enhanced peat accumulation in the bog centre, hence the name ‘raised’ bog. Blanket bogs (Figure 1.2B) mostly occur directly on mineral soils in cool, very wet and usually oceanic climates with lower summer temperatures and higher precipitation rates than raised bogs (usually >1200 mm/year; Tallis, 1998). These conditions allow blanket bogs to cover extensive parts of both the lowland and mountainous landscape without being restricted to topographical depressions (Moore, 2002). Accordingly, blanket bogs derive their name from appearance and distribution: covering the landscape like a blanket.

A major and crucial vegetational component of both raised and blanket bogs is the presence of peat mosses (bryophytes from the genus *Sphagnum*). Peat mosses thrive in peatlands largely because they facilitate their own survival by creating recalcitrant, poorly permeable and acidic litter that maintains high water tables and inhibits vascular plant growth (Aerts et al., 1999; Berendse et al., 2001; Hájek et al., 2011; Hobbie, 1996; van Breemen, 1995; Verhoeven & Liefveld, 1997). As a result, peat mosses not only drive peat accumulation in these ecosystems, but can contribute up to 90% of organic matter in peat (Loisel et al., 2014; Turetsky, 2003), giving them a crucial role in the formation, stability, and resilience of bogs (Turetsky et al., 2012). Nevertheless, the cover of peat mosses is more often than not much lower in blanket bogs than in raised bogs. This is most likely related to more variable water tables caused by the irregular topography and steeper slopes in blanket bogs (Schouten, 1984). Therefore, peat mosses only grow vigorously in depressions of the blanket bog topography, where surface water accumulates, and impeded drainage maintains permanently high-water tables. Besides, raised bogs have typically formed over longer time-periods and more independently of the topography over which they lay than raised bogs (Moore, 2002). For these reasons, raised bogs generally contain deeper peat deposits than blanket bogs (Schouten, 1984).

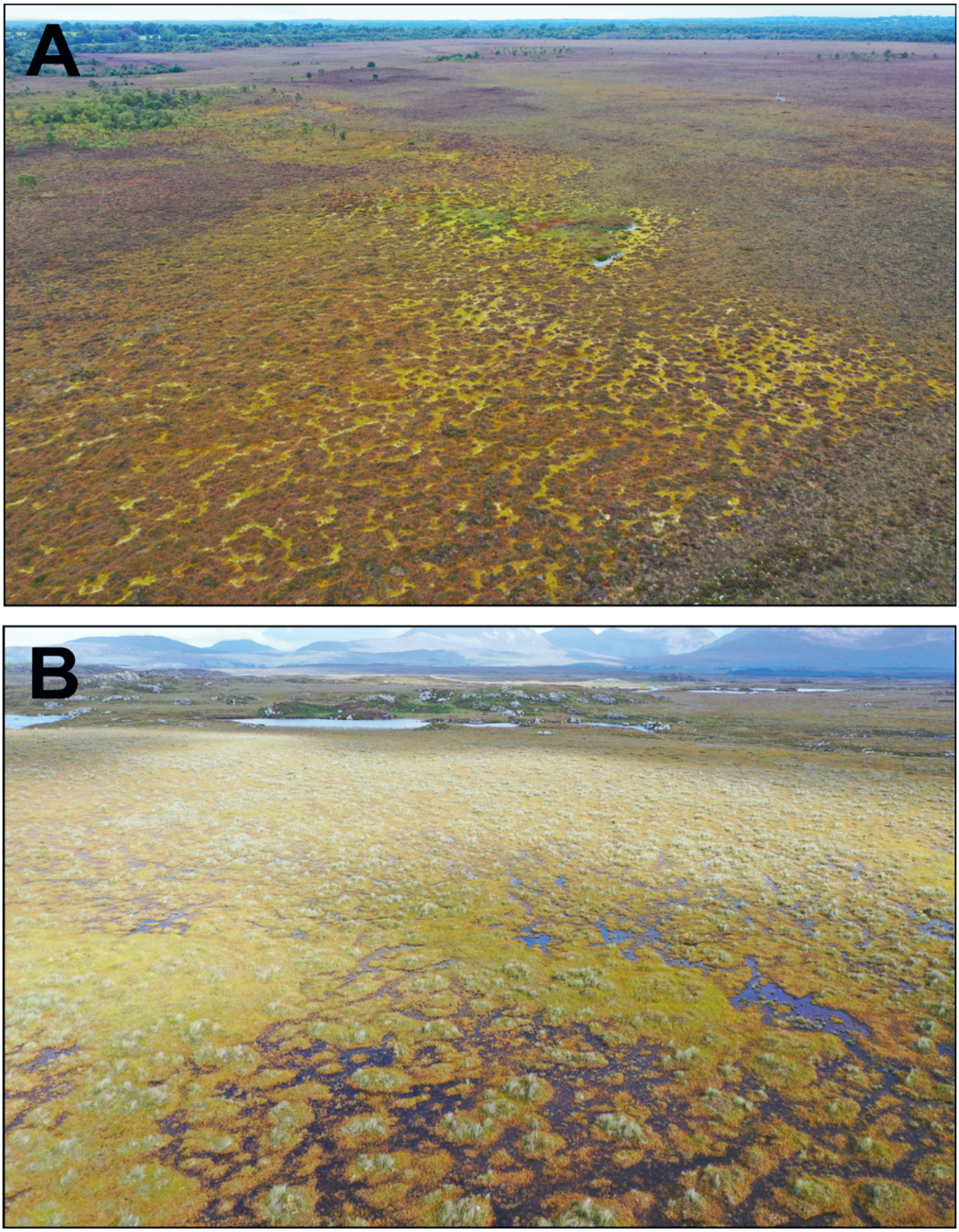


Figure 1.2 Example of the two different type of peatlands that were studied in this thesis: **A)** a drone image of Clara raised bog in the Irish Midlands (Co. Offaly) with different types of vegetation communities, and **B)** an image of Roundstone blanket bog in western Ireland (Co. Roscommon) with characteristic tear pools.

1.2 Peatland functions and services

1.2.1 Recent history of peatland uses in Europe

People and peatlands have been long been connected by an intimate relationship of cultural development, and the abundance of bog bodies, tools, ornaments, weapons and other archaeological remains retrieved from these ecosystems are a perfect testament to this (Joosten, 2009a). However, whereas early hunter-gatherers and traditional farmers relied upon or even fully depended on peatlands for their sustenance (Silvius et al., 2008), peatlands were also viewed as dangerous, inhospitable and purposeless places (Flint & Jennings, 2020). Initially, their limited accessibility inhibited large-scale human activity, and often turned them into political, cultural and language borders (Silvius et al., 2008). However, lack of appreciation and need for careful development soon resulted in peatlands being exploited for short-term economic interests. The high population density and climatic suitability for agriculture made peatlands in Europe particularly susceptible to human use for their provisioning services (Joosten, 2016).

Some of the main human uses of peatlands in Europe for their provisioning services were and still are drainage for agriculture, cattle ranching and forestry, as well as peat extraction for energy production, heating and horticulture (Joosten, 2016; Silvius et al., 2008). Particularly, about 125.000km^2 of European peat soils are drained for agricultural production, with extensive areas in Russia, Germany, Belarus, Poland and Ukraine (Joosten & Clarke, 2002). In countries like the Netherlands and Germany, the percentage of peatland conversion for agriculture is even up to 85% of the total peatland area (Rydin & Jeglum, 2013). Yet, timber, fuel wood and pulp are the products for which the largest peatland areas have historically been drained, with the largest booms in forestry around the 1970s in Finland, Russia and Sweden (Paavilainen & Päivänen, 1995), but also in other European countries like the Baltic states, Ireland and Scotland (Joosten, 2016; Rydin & Jeglum, 2013; Figure 1.A, C). While peat extraction for energy production and heating is being phased out by 2030 in most major remaining extracting countries like Ireland and Finland (Hirschler & Osterburg, 2022), it is still carried out on domestic and commercial scales (Figure 1.3A, C, D), totalling about 2000km^2 in those countries, as well as in countries like Scotland, Sweden, Estonia and Belarus (Joosten & Clarke, 2002). In the last decade, still about 5–7% of primary energy consumption in Ireland and Finland relied on peat combustion (Gadonneix et al., 2013). The Netherlands even went so far that they had already extracted 95% of their total peatland area (~2000km^2) for fuel supply at the start of the 20th century (De Zeeuw, 1978). Similar areas as for energy production and heating are consumed for the horticultural industry (Figure 1.3B), where the increasingly growing demand for permanently available vegetables, fruits and flowers has led to extraction of slightly humified peat as a growing medium for these agricultural products in both global and hobby markets (Joosten, 2016).

Even though available estimates suggest that some 85% of the global peatland area is still in largely natural condition (Bonn et al., 2016), about 50% of peatland area in the European Union is currently degraded (Tanneberger, Moen, et al., 2021). Strikingly, this percentage increases to 68% for the Atlantic bog region, and even up to 99% for individual countries like the Netherlands and Ireland (National Parks and Wildlife Service, 2018; Tanneberger, Moen, et al., 2021). Besides, an additional 5000km^2 (~0.1%) of global peatlands is still destroyed by human activities on a yearly basis, and peat volumes are declining by approximately 0.2% per year (Joosten, 2009b). Regrettably, our track-record of peatland exploitation in Europe shows that their large-scale abundance is by no means a guarantee for their survival.

1.2.2 New perspectives on peatland services and disservices

There has been a long-standing and strongly biased focus on the direct provisioning services of peatlands. As a result, most supporting, cultural and regulating services, as well as the destructive effects of peatland exploitation on these services have long been undervalued, ignored or gone unnoticed (Page & Baird, 2016; Wichmann et al., 2016). However, recent advances in scientific research have given us a deeper understanding of the intricate ecological processes occurring within peatlands, as well as their functions. This has invariably resulted in greater appreciation of the extremely large range of other ecosystem services peatland functions provide at all local, regional and global scales (Rydin & Jeglum, 2013). For instance, peatlands contain many rare and unique plant species that occur exclusively in peatlands and have adapted to their extreme environmental conditions by developing specialised physiology, anatomy, morphology, and life cycles (Minayeva et al., 2017; Figure 1.3E). These vegetation communities are often also climax communities, which means they are the product of long-term ecosystem development and succession. Peatlands can also regulate biodiversity and climate extremes far beyond their own borders by buffering the hydrology and microclimate of adjacent areas (Joosten & Clarke, 2002; Minayeva et al., 2008). This way, they can act as refugia that provide shelter, food, breeding grounds, and stepping stones for migration during periods of disturbance (Minayeva et al., 2008). Peatlands also purify water and mitigate flooding and drought through their disproportionally large capacity for water storage, recharge and discharge (Bonn et al., 2016). Nevertheless, this ‘sponge’ function cannot be upheld unconditionally because many of the water retaining capacities of peatlands are related to high peat moss cover (Joosten & Clarke, 2002; Price et al., 2016). Furthermore, peatlands are of personal and collective cultural value as places related to heritage, education, sense of place, recreation and spirituality (Bonn et al., 2016; Flood et al., 2021; Figure 1.3F). Lastly, they sequester so much organic matter through peat accumulation (see Figure 1.3B, D) that they store approximately one-third of the global terrestrial soil carbon (Rydin & Jeglum, 2013; Yu et al., 2010), Therefore, peatlands serve above all a crucial global climate-regulating ecosystem service.

Not only do peatlands provide a variety of ecosystem services, but it should also be noted that peatland degradation leads to loss of these services, and can even become disservices. For instance, loss of services includes biodiversity decline (Lõhmus et al., 2015; Tanneberger, Appulo, et al., 2021) and reduced recreational value (Byg et al., 2017; Tanneberger, Appulo, et al., 2021). Some disservices are impairment of hydrological processes (Stachowicz et al., 2022), reductions in water quality from nutrient loading (Kosenius et al., 2013) and modification of energy flows, nutrient cycles and greenhouse gas emissions (Escobar et al., 2022; Makrickas et al., 2023). In fact, greenhouse gas emissions from drained and degraded peatlands are estimated to constitute about 5% of all global annual anthropogenic activities (Ma et al., 2022). Other disservices include peat subsidence (Ma et al., 2022), increased wildfire risk (Nelson et al., 2021; Turetsky et al., 2015) which in case of wildfire affects air quality in surrounding areas (Shaposhnikov et al., 2014; Tinling et al., 2016), and negative impacts on human well-being and/or community spirit through reduced ecosystem quality and recreational value (Byg et al., 2017; Tanneberger, Appulo, et al., 2021). Peatland disservices will most likely continue to increase until peatlands are rewetted or restored. This highlights that the value of healthy peatlands is not only determined by the services they provide, but also by the disservices they prevent or mitigate.

1.2.3 From exploitation to conservation and restoration

Because of our newly gained knowledge about their services and disservices, the importance of peatlands and their need for conservation and restoration is increasingly recognised at a global scale. In Europe, this has translated into large investments and conservation projects aimed at reversing the damage caused by long-term peatland exploitation (Andersen et al., 2017; 1.3G, H). However, peatland conservation and restoration often clash with their conventional use for provisioning services. This is because areas where peatlands remain in Europe are often densely populated, with pressures from competing land-uses and contrasting public perceptions about the role of peatlands and peatland management (Bain et al., 2011; Bullock & Collier, 2011; Byg et al., 2017; Chapman et al., 2003; Rawlins & Morris, 2010). To address such conflicts, but also to be able to assess restoration “success” and to account for the large investments made in peatland protection, we need an integrated understanding of both the ecological and socio-economic impacts of specific management techniques to optimise benefits for both nature and society (Andersen et al., 2017; Glenk & Martin-Ortega, 2018).

Adopting an ecosystem services approach could be advantageous to help acknowledge the wider relevance of peatland protection for various stakeholders while simultaneously placing local action into a more global context (Glenk & Martin-Ortega, 2018; Joosten, 2016). Here, specifically payments for ecosystem services could correct and create markets through capturing the benefits of and raising new funds for peatland protection (Glenk & Martin-Ortega, 2018; Wichmann et al., 2016). While most non-market cost-benefit analyses of peatland ecosystem services highlight considerable economic benefits and welfare enhancements through peatland protection, restoration and conservation (Glenk & Martin-Ortega, 2018; Makrickas et al., 2023), only the climate regulating function of peatlands has been put to the market until now (Bonn et al., 2014; Tanneberger et al., 2024). Carbon markets are particularly appealing for ecosystem service payment schemes because they are not spatially dependent like many other regulating, supporting and cultural services (Glenk et al., 2014). However, including other ecosystems besides climate regulation like biodiversity could give peatland carbon credits a competitive edge above other (potentially cheaper) carbon credits (Buck & Palumbo-Compton, 2022). Irrespective of the service or disservice at hand, using ecosystem services as a means for peatland protection requires development of accurate, standardised and long-term monitoring schemes that target the multiple ecosystem services peatlands provide (Andersen et al., 2017; Minasny et al., 2023; Reed et al., 2022).

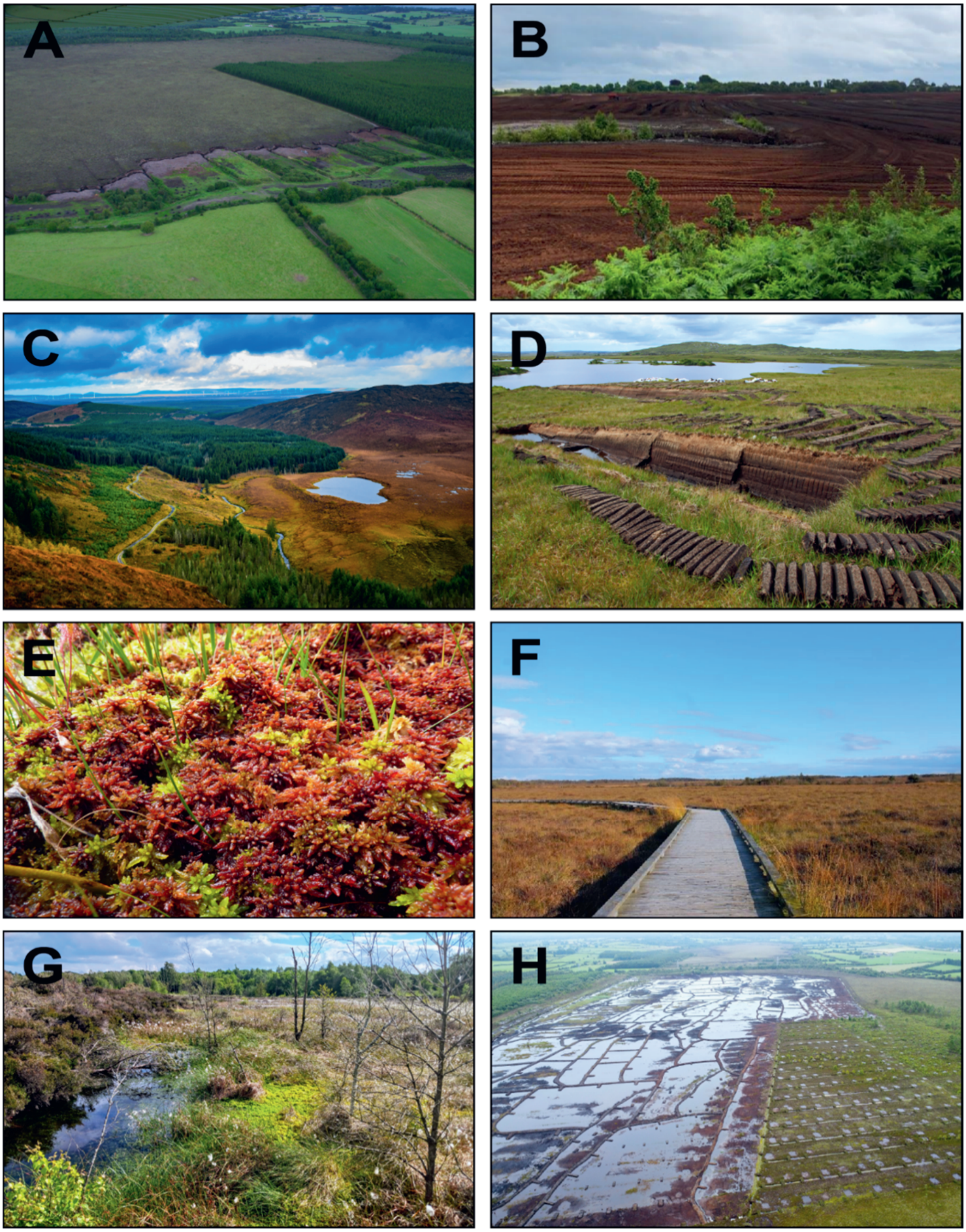


Figure 1.3 Peatland services in Ireland: **A)** a raised bog with domestic peat cutting at the margins and partial afforestation, **B)** commercial peat extraction in a raised bog, **C)** afforestation in a blanket bog, **D)** domestic peat cutting in a blanket bog, **E)** several colourful peat moss species, **F)** boardwalk at Clara bog, **G)** restoration at a raised bog margin, **H)** large-scale rewetting of a raised bog. Photo credits to Fernando Fernandez (A, E, F, G, H), Colin Butler (C) and Graham Higgs (D).

1.3 Peatland vegetation patterns

1.3.1 Peatland microforms

The extreme surface conditions of peatlands give rise to unique types of open vegetation that cover the nearly the whole peatland landscape. While their overall plant species diversity is indeed generally low compared to mineral soil ecosystems in the same biogeographic zone (Minayeva et al., 2008), peatlands are far from homogeneous ecosystems. On the contrary, peatland surfaces exhibit intricate mosaics of microtopographic irregularities in the landscape called microforms (Figure 1.4B, C, D), the spatial organisation of which is readily observed due to the distinctive vegetation associated with them. Peatland microforms range from open water pools, where the peat surface is always below the water table, to wet hollows, to moist lawns that regularly inundate, to dry hummocks where the peat surface reaches up to 50cm above the water table (Rydin & Jeglum, 2013; Figure 1.4D). Changes in water table, nutrient availability and pH levels along this microtopographic gradient from open water to hummock create ecological niches for different plant species sharing adaptations to the same local environmental conditions. Microforms thus represent a distinct set of plant species and/or plant functional types that can be recognized as a coherent unit (see also Table 2.1). For instance, open water pools are generally sparsely vegetated, but sometimes harbour aquatic plant species. Hollows contain aquatic peat moss species occasionally interspersed with sedges. Lawns are typical transition zones between hollows and hummocks and contain more intermediately drought-adapted peat moss species, occasionally interspersed with sedges, forbs, and some shrubs. Finally, hummocks are dominated by shrubs, lichen, graminoids, and more drought-adapted peat mosses, and harbour trees in some types of peatlands (Table 2.1).

1.3.2 The development, long-term stability and potentially rapid dynamics of microforms

Peatland microforms can exhibit remarkable resistance and resilience to changes in environmental and climatic conditions (Belyea & Clymo, 2001; Nungesser, 2003). Especially when these conditions are stable, microforms can even exist in the same place for centuries to millennia (Baird et al., 2016). It is therefore thought that development and long-term stability of microforms is driven by feedbacks between vegetation and abiotic factors like pH, light availability, water table depth, nutrients and temperature (Eppinga, Rietkerk, et al., 2009; Waddington et al., 2015). For instance, while we know that slow-growing peat mosses facilitate their own perpetuation by keeping the environment wet, the more productive shrubs and trees instead dry and aerate the peat soil by interception and transpiration (Eppinga, Rietkerk, et al., 2009). Besides, vascular plants accumulate nutrients from the surrounding environment through advective transport and their root systems (Eppinga et al., 2008; Rietkerk et al., 2004), amplifying suitable conditions for further vascular plant growth. Through such feedback mechanisms, the physiological characteristics of both peat mosses and vascular plants change their local environmental conditions in a way that favours their own persistence and proliferation at the expense of the other. Microforms eventually develop when initial differences in peat characteristics and rates of peat accumulation resulting from these contrasting growth strategies can amplify over time under stable environmental conditions.

While peatlands are generally characterised as resilient ecosystems to climatic and environmental changes, many studies have also found that peatlands can undergo rapid structural shifts in vegetation even in response to small external forcing when certain environmental thresholds are passed that disproportionally favour one microform over the other (e.g. Belyea, 2013; Belyea & Malmer, 2004; Dieleman et al., 2015; Page & Baird, 2016; Wilson & Agnew, 1992). Global surface temperatures have already increased by approximately 0.2°C every decade since the 1980’s (IPCC, 2023), and northern latitudes have warmed at more than double the rate of lower latitudes (Cohen et al., 2014; Overland et al., 2014). Besides, despite an increase in precipitation in some areas, available moisture in most peatlands is likely to decrease notably following an increase in evaporative demand through these increasing temperatures (Gallego-Sala & Colin Prentice, 2013; Helbig et al., 2020; Swindles et al., 2019). This may potentially lead to shifts in dominant vegetation types. For example, some studies show that production of peat mosses was strongly inhibited by elevated temperatures and reduced precipitation (e.g. Bragazza et al., 2016; Dieleman et al., 2015; Jassey et al., 2013; Norby et al., 2019; Rastogi et al., 2019). Moreover, persistent lowering of the water table could lead to expansion of hummock peat mosses at the cost of hollow species (Breeuwer et al., 2009; Miller et al., 2015; Robroek, Limpens, Breeuwer, & Schouten, 2007) due to their higher water retention capacity (Bu et al., 2013; McCarter & Price, 2014; Turetsky et al., 2008). Warmer and drier conditions also result in increased competitive capacity of shrubs over mosses and graminoids in a positive feedback that further enables shrub expansion (Bragazza et al., 2013; Holmgren et al., 2015). Conversely, increased shrub growth may also moderate temperature and evaporative losses through shading (Hedwall et al., 2017; Kettridge et al., 2013; Limpens et al., 2014) and hereby promote growth of peat mosses under shrub canopies (Walker et al., 2015). Still, our knowledge about the sensitivity of peatland vegetation to external pressures remains highly uncertain because it depends on the magnitude and direction of environmental changes in combination with the strength of their internal regulation, which may take decades to take effect (Swindles et al., 2012).

1.3.3 What are vegetation patterns?

I define peatland vegetation patterns in this thesis as the composition, diversity and spatial organisation of microforms and their associated vegetation across the peatland landscape. However, it is important to note that peatland vegetation patterns can be expressed in various ways depending on the hierarchical spatial scale at which you evaluate and categorise them. For instance, individual microforms are typically 1–10m in size, and can stretch from small, isolated patches of vegetation to more expansive features in the landscape (Belyea & Baird, 2006; Figure 1.4A, B). At this microform-scale or fine-scale, individual plant species or plant functional types within a microform can be aggregated as a vegetation pattern, or all plants of the same microform can be aggregated into a coherent unit. Microforms also appear across a peatland in regular vegetation complexes with spatial patterns of varying proportions. These vegetation complexes generally range from 10–100m and are also called the microtope scale (Belyea & Baird, 2006; Figure 1.4B). Microtopes reflect hydrological conditions in different sections of a peatland, like water level, nutrient supply, drainage and surface inclination (Schouten, 2002). Here, level parts, which often occur in the centre of a raised bog or topographical depressions of a blanket bog, generally contain extensive areas with distinct microform gradients ranging from open water pools to high hummocks. Moving from the flat centre or topographical depressions towards the sloping sections of a peatland, microforms typically become less distinct, and microtopes mostly contain only lawns and hummocks.

The larger extent and distribution of different microtopes throughout a peatland often happens at spatial scales of about 100–1000m and are indicative of peatland-wide hydrological processes and environmental gradients (Figure 1.4B). In pristine raised bogs, these so-called mesotopes or habitats theoretically reflect a relatively concentric (circularly zoned) pattern from centre to margin, but habitats reflecting both dry and wet surface conditions can occur in different sections of a peatland depending on local hydrological conditions. Lastly, individual peatlands can be aggregated to the level of macrotopes (~1000–10000m), which is a hierarchical spatial scale that encompasses the distribution and characteristics of a peatland within a broader assemblage of surrounding peatlands and/or non-peatland ecosystems (Belyea & Baird, 2006). This scale is also called the landscape-scale or peatland-scale, as I define it in this thesis. The focus of my thesis is on vegetation patterns occurring at all microform-, microtope-, and mesotope- and macrotope-scales.

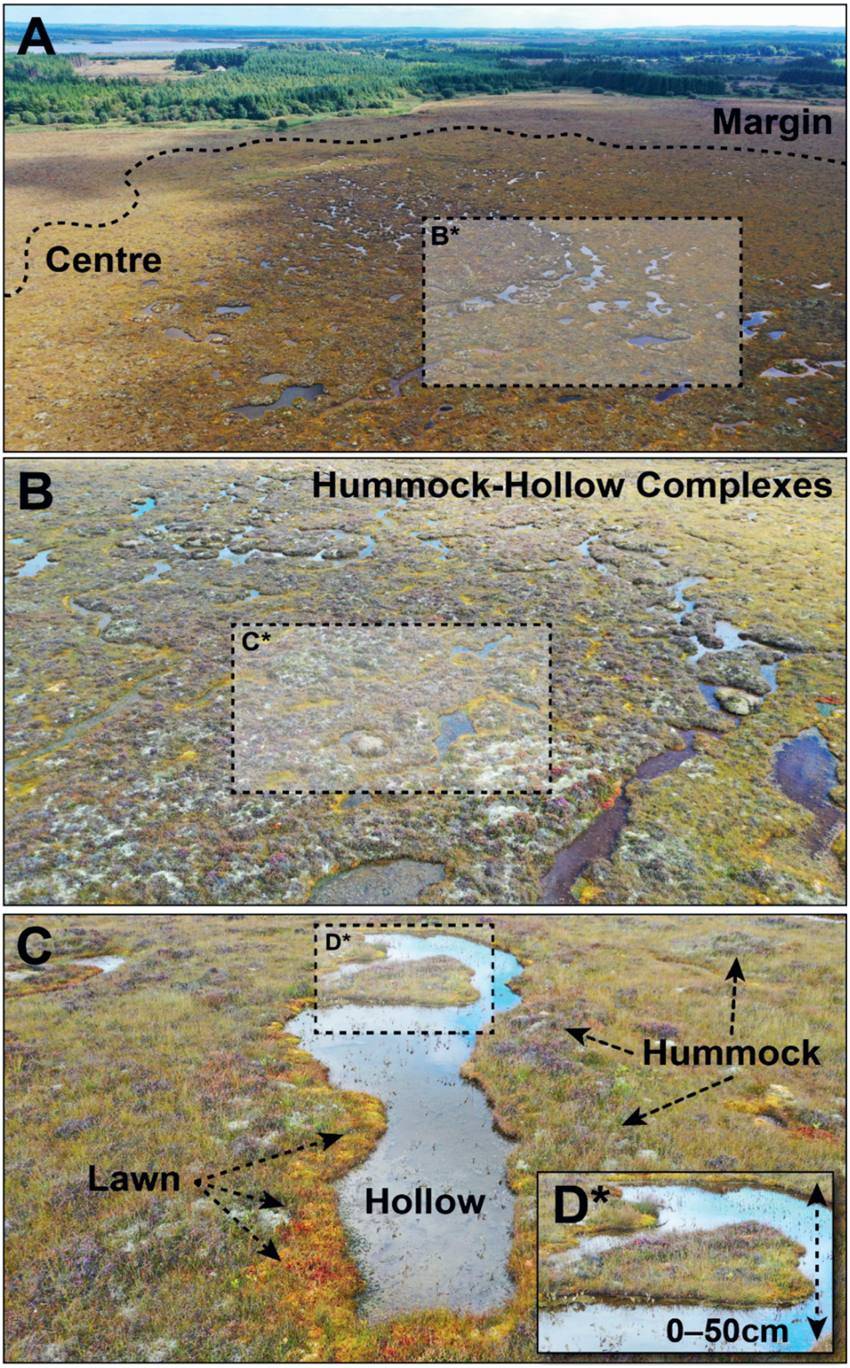


Figure 1.4 Some of the hierarchical spatial scales of peatland vegetation patterns. Represented are **A)** the mesotope scale with peatland centre and margin, **B)** the microtope scale with hummock-hollow complexes, **C)** characteristic microforms, and **D)** a microform ranging from open water to a hummock.

1.3.4 Vegetation patterns as ecological indicator

Because peatlands are complex ecosystems, it is often hard or even impossible to characterize their whole functioning and thus services through direct measurements alone. Their spatial characteristics (i.e. size, continuity, inaccessibility, sensitivity and isolation) often make fieldwork costly and intensive. Besides, the intricacy of their interactions and feedbacks require many different measurements. Combined, this frequently impairs exhaustive analyses of all ecological aspects of a peatland at a given time. To address such issues, environmental managers often look for specific and measurable variables that are representative of the broader state or dynamics of the ecosystem. Such variables are also called ecological indicators. The development and application of ecological indicators has existed in environmental management for about 65 years (Niemi & McDonald, 2004). However, in peatland science the development of a comprehensive and unified process that can be used by experts to standardise the collection, management, analysis, reporting and re-use of data of ecological indicators has only recently been initiated (Minasny et al., 2023; Reed et al., 2022). For instance, the EU Habitats Directive distinguishes a total of thirteen broad habitat types for all peatlands in Europe, among which Blanket bogs (code: 7130), Active raised bogs (code: 7110) and Degraded raised bogs still capable of regeneration (code: 7120) are most applicable for this thesis.

Vegetation patterns are theoretically well-suited as an ecological indicator in peatlands because they are both a consequence and driver of local environmental conditions at multiple spatial scales. Therefore, the presence or absence of specific types of vegetation patterns offers a near direct insight into the environmental conditions beneath the peat surface, like the water table, nutrient availability, soil temperature and pH levels. The close relationship between peatland vegetation patterns and environmental conditions also plays a crucial role in ecosystem functioning. For these reasons, fine-scale vegetation patterns like microforms and plant functional types and habitats have independently been put forward as high priority ecological indicators for various reasons. Particularly, fine-scale vegetation patterns strongly drive carbon dynamics because of large differences in peat accumulation and decomposition rates between the plant functional types associated with specific microforms (Aerts et al., 1999; Goud et al., 2017; Johnson & Damman, 1991; Laine et al., 2012; Turetsky et al., 2008). Microforms also drive carbon fluxes because the ratio of methane to carbon-dioxide emissions from soil respiration increases from hummock to hollow due a decline in water table depth (Bubier et al., 1993; Krohn et al., 2017; Laine et al., 2007; Lunt et al., 2019; Waddington & Roulet, 1996). Besides, differences in peat accumulation and decomposition rates make peat on hummocks more dense and less permeable than lawn and hollow peat (Arens, 2017; Lapen et al., 2005; Waddington et al., 2010). This controls peatland hydrology because hummocks act as physical barriers to lateral water flow, retaining water in the system through both their presence and spatial organisation (Arens, 2017; Waddington et al., 2015). Lastly, diversity in plant functional types also increases the carbon sink function of a peatland (Robroek et al., 2017), and facilitates reorganisation through lateral expansion and contraction of microforms and their associated plant species. In this way, diverse vegetation patterns may provide peatlands with resilience to changing climatic conditions (Belyea & Clymo, 2001).

On a larger hierarchical spatial scale, the extent and distribution of different peatland habitats affect both nutrient and water dynamics (Schouten, 2002; van der Schaaf, 2002). Hereby, habitats are not only indicative of peatland-wide water table depth and carbon fluxes (Regan et al., 2020; Swenson et al., 2019), but they are also an indicator of the overall species diversity a peatland can support because different habitats can host different plant species. These examples alone already exemplify that the stability and/or dynamics of fine-scale vegetation patterns and the larger-scale habitats they form have high potential to be used as an ecological indicator for broader ecosystem functioning and services in peatlands like carbon fluxes, biodiversity, water storage and water quality. However, translating the potential of vegetation patterns as an ecological indicator into practice requires more than just a strong innate connection to specific peatland functions. It also requires that peatland vegetation patterns themselves can be characterised at the large spatial scales by which they occur in the broader landscape, and that their spatiotemporal dynamics occur at timescales that are relevant for use in monitoring schemes of peatland services.

1.4 Remote sensing for monitoring peatland vegetation patterns

1.4.1 Why use remote sensing in peatlands?

Characterising and mapping peatland vegetation patterns has traditionally been carried out mostly using field-based approaches (Minasny et al., 2023; Schouten, 1984, 1990). While field surveys lead to highly detailed data, and resulted in the advancements of fundamental peatland knowledge that can now be applied, field-based research is often severely limited by scale and costs. Hence, with field-based approaches alone it is unfeasible to upscale findings on vegetation patterns and their associated functions to the spatial scale at which they occur in the landscape. This is especially relevant when considering the generally large, continuous, inaccessible, sensitive and isolated nature of most peatlands worldwide. Due to these limitations, but also due to rapid development and greater availability of high-quality remote sensing platforms, datasets and open-source software, the use of remote sensing analyses as an extension for field-based peatland monitoring has gained substantial popularity in the last decades (Czapiewski & Szumińska, 2022; Minasny et al., 2019). Loosely defined, remote sensing revolves around acquiring imagery of the Earths' surface from a distance using various platforms like satellites, aircrafts and unmanned aerial vehicles or drones. These platforms are equipped with camera sensors like the visible spectrum, infrared, radar, thermal, hyperspectral and Light Detecting and Radar (LiDAR) which can capture spectral, spatial and topographical information. This imagery can subsequently be analysed to extract information about the environmental conditions of the Earths' surface and underlying layers. Remote sensing is allowing us to map and monitor new, larger and difficult to reach peatland areas with greater detail and accuracy than would ever be possible without it. This is substantially enhancing our knowledge about their global functioning and services.

The general advantages of remote sensing over field-based approaches and their complementary features are often already appealing enough to rationalise its use, but the potential role of remote sensing in peatlands is further enhanced by its inherent suitability for vegetation mapping. Particularly, the contrasting biogeochemical and hydrological conditions of microforms lead to relatively clustered vegetation patterning. This also acts as a strong filter on both the spatial and spectral properties of vegetation patterns, as the plant species and plant functional types associated with different microforms often differ markedly from one another (Bubier et al., 1997; Harris & Bryant, 2009; McPartland et al., 2019; Schaepman-Strub et al., 2009). This allows for differentiation of many different vegetation pattern classes at the same time. Besides, the aggregated spectral reflectance signature of habitats is also typically well reflected by the proportions of fine-scale vegetation patterns occurring within it (Bhatnagar et al., 2021). The availability of topographical data in remote sensing is also extremely valuable in peatland mapping because it can capture the macro- and microtopographical gradients of peatlands that are so important in driving their vegetation patterns. And last but not least, peatlands and especially Atlantic peatlands are often relatively flat and tree-less, which is known to vastly improve the accuracy and consistency of generated digital elevation models (Czapiewski, 2022; Lovitt et al., 2017).

1.4.2 Advantages and limitations of different remote sensing platforms

While peatlands are theoretically well-suited for remote sensing of vegetation patterns, its overall usefulness for monitoring functions and services is still largely determined by the accuracy, efficiency and repeatability by which imagery is acquired and by which relevant information can be extracted from it. Indeed, the extremely large variety of different peatland remote sensing studies that have been carried out in the last two decades highlight that the peatland remote sensing community is currently still exploring and establishing its most optimal use (Abdelmajeed & Juszczak, 2024; Czapiewski & Szumińska, 2022; Minasny et al., 2019). Particularly, most recent remote sensing studies in peatlands were carried out with passive satellite imagery, which is one of the most accessible and widely used remote sensing platforms. It has the advantage of being mainly free, with global coverage, systematic acquisition and many different spectral bands (Figure 1.5). Yet, usability of satellite imagery is dependent on cloud cover and atmospheric conditions, which can be obstructive in peatland areas. Besides, most of these satellites currently lack the spatial resolution to directly characterise most fine-scale vegetation patterns at the fine and heterogeneous spatial scales by which they occur in the peatland landscape (Figure 1.5). For example, the spatial resolution of multispectral imagery from the Landsat-9 and Sentinel-2 satellites, which are currently the most common freely available satellites, are 15–30m and 10–20m respectively. Where satellite imagery with sub-meter spatial resolutions does exist, it is often highly costly. Alternatively, airborne remote sensing such as with aircraft mounted sensors was also often used as a more regional remote sensing platform for peatland monitoring (Abdelmajeed & Juszczak, 2024; Czapiewski & Szumińska, 2022). The advantage of airborne imagery over satellites is that it is regularly equipped with both passive and active sensors and has higher spatial resolutions that can range from a few centimetres to a couple of meters, while still being able to cover large areas quickly under a wide range of atmospheric conditions. However, its use is often restricted due to high costs, mobilisation time and the need for specialised aircraft and trained personnel (Carless et al., 2019; Figure 1.5).

In addition to airborne and satellite remote sensing, which have existed since the mid-to-late 20th century, drone-based remote sensing has only recently emerged as a versatile new tool in spatial ecology (Anderson & Gaston, 2013; Crutsinger et al., 2016; Cruzan et al., 2016; Manfreda et al., 2018; Figure 1.5). In fact, its use experienced a remarkable rise in popularity in peatland studies in the last decade (Abdelmajeed & Juszczak, 2024). Drone-based remote sensing involves imagery acquisition and analysis using sensors equipped on small unmanned aerial vehicles or drones. Drones in spatial ecology range from small, relatively inexpensive and flexible consumer-grade drones to larger and often customised research-grade drones with additional payloads and/or sensors. Both drone systems typically have extremely high, centimetre level spatial resolution, and their advanced technology allows for development of similarly high-resolution digital elevation models through photogrammetry. Accordingly, they can already capture the fine-scale heterogeneity of peatland microtopography and their vegetation patterns at unprecedented level of detail. Besides, drones will evolve to become even smaller, lighter, more efficient and cheaper in the upcoming years (Anderson & Gaston, 2013; Crutsinger et al., 2016; Manfreda et al., 2018; Vergouw et al., 2016). Together with coinciding technological advancements in sensors, global positioning systems, flight stability and automated flight planning, this will likely continue to make drones more accessible in spatial ecology for a wide variety of users. Nevertheless, as with other remote sensing platforms, drones too are limited by extreme weather conditions occurring in high latitude areas like peatlands during some time-periods of the year, such as high wind, fog, rain, heat, and cold (Assmann et al., 2019; Duffy et al., 2018). Still, because of their flexibility, general affordability and extraordinary spatial, spectral and topographical resolution, drones could form an ideal bridge between field-based research and satellite remote sensing for mapping and monitoring peatland vegetation patterns and their associated functions.

Figure 1.5 Some of the major advantages and limitations of commonly used remote sensing platforms in relation to field surveys for mapping and monitoring of peatland vegetation patterns. Represented are field surveys, unmanned aerial vehicles (or drones), airborne imagery and earth observation satellites, as well as the altitude by which these platforms generally capture imagery.

1.5 Knowledge gaps in drone-based mapping of peatland vegetation patterns

The strong relationship between peatland vegetation patterns and functions highlights their potential role as ecological indicators for large-scale monitoring of ecosystem services. However, this not only requires mapping approaches that can accurately capture vegetation patterns at the fine and heterogeneous scales at which they occur and by which their functions operate, but also that can efficiently be expanded from pilot sites to the generally large, continuous, inaccessible, sensitive and isolated areas most peatlands occupy in the broader landscape. While peatland vegetation patterns have already been mapped successfully in previous recent drone studies (e.g. Beyer et al., 2019; Bhatnagar et al., 2020, 2021; Knoth et al., 2013; Lehmann et al., 2016; Palace et al., 2018; Räsänen et al., 2019; Räsänen & Virtanen, 2019; Simpson et al., 2024), these were often literally and figuratively pilot studies. They studied a large variety of peatlands and employed a similarly large variety of approaches. Yet, they often lacked a clear, comprehensive and standardised justification or rationale for the choice of drone and sensors, the parameters that were used during both capturing and processing of the imagery and methodological steps that were undertaken during analyses. This often resulted in variable accuracies, challenges with upscaling, or both. The relatively disparate and indiscriminate use of drone-based vegetation pattern mapping approaches in these studies is possibly explained by the novelty of drone-based remote sensing in peatlands (Abdelmajeed & Juszczak, 2024), as most optimal uses are still being explored. Yet, all studies highlight the pivotal importance of developing guidelines for mapping peatland vegetation patterns, especially because drone-based remote sensing can quickly become unnecessarily costly, complex, computationally heavy and time-consuming depending on the adopted approach.

Currently, the overall absence of consistent documentation and comparisons of different drone-based approaches for mapping peatland vegetation patterns results in large knowledge gaps in the requirements for accurate and efficient mapping. This is hampering the upscaling of drone-based approaches that is often required to monitor peatland vegetation patterns as ecological indicators. Besides, lack of development towards standardised frameworks that can be employed or used as a starting point from which to build on is also limiting the general applicability of drones in the field since there may be a tendency to use the most advanced techniques to receive the most optimal results. Yet, it is still highly questionable whether analyses based on imagery from expensive research-grade drones with additional payloads and/or sensors noteworthily outperform the much more accessible consumer-grade drones for the average needs in spatial ecology, if at all. These knowledge gaps clearly stress the demand and responsibility for comparative testing.

1.6 Objectives and aims of this thesis

My thesis responds to the knowledge gaps posed in section 1.5 by iteratively developing an accessible consumer-grade drone-based remote sensing approach. The main objective is to iteratively refine this approach so that at length it can be used to accurately and efficiently map plant functional types, microforms and habitats at the peatland-scale in various contrasting peatlands and peatland types. We focus specifically on these three hierarchical spatial scales because they are commonly used when translating peatland vegetation patterns to functions. All imagery was acquired using a DJI Mavic 2 Pro consumer-grade drone with only bands in the visible spectrum, and the mapping approach was tailored so all analyses could be carried out on a personal computer. Besides, the definition of efficiency in this thesis extends beyond the time needed for data collection, processing and analysis, and also relates to overall resource utilisation, ease-of-use, flexibility, repeatability and scalability.

Through development and refinement of this consumer-grade drone-based mapping approach, I aim to 1) provide novel and comprehensive insights into the strengths, limitations and requirements of drones in large-scale mapping of peatland vegetation patterns. This way, I ultimately aim to 2) advance the development of accurate, efficient and standardised monitoring workflows that researchers, environmental managers, policymakers, local communities and other interested users can employ or build upon to assess the spatiotemporal dynamics of peatland vegetation patterns, as well as their functions and the services they represent. I believe this will lead to more effective peatland protection all over the globe.

1.7 Thesis outline

All field and drone surveys were conducted in a total of fifteen peatlands distributed throughout central Ireland. We selected these peatlands for this thesis research based on their contrasting vegetation patterns, and because of previous vegetation mapping work conducted by Schouten (1984) and the Irish National Parks and Wildlife Service (NPWS) that could be used as reference datasets.

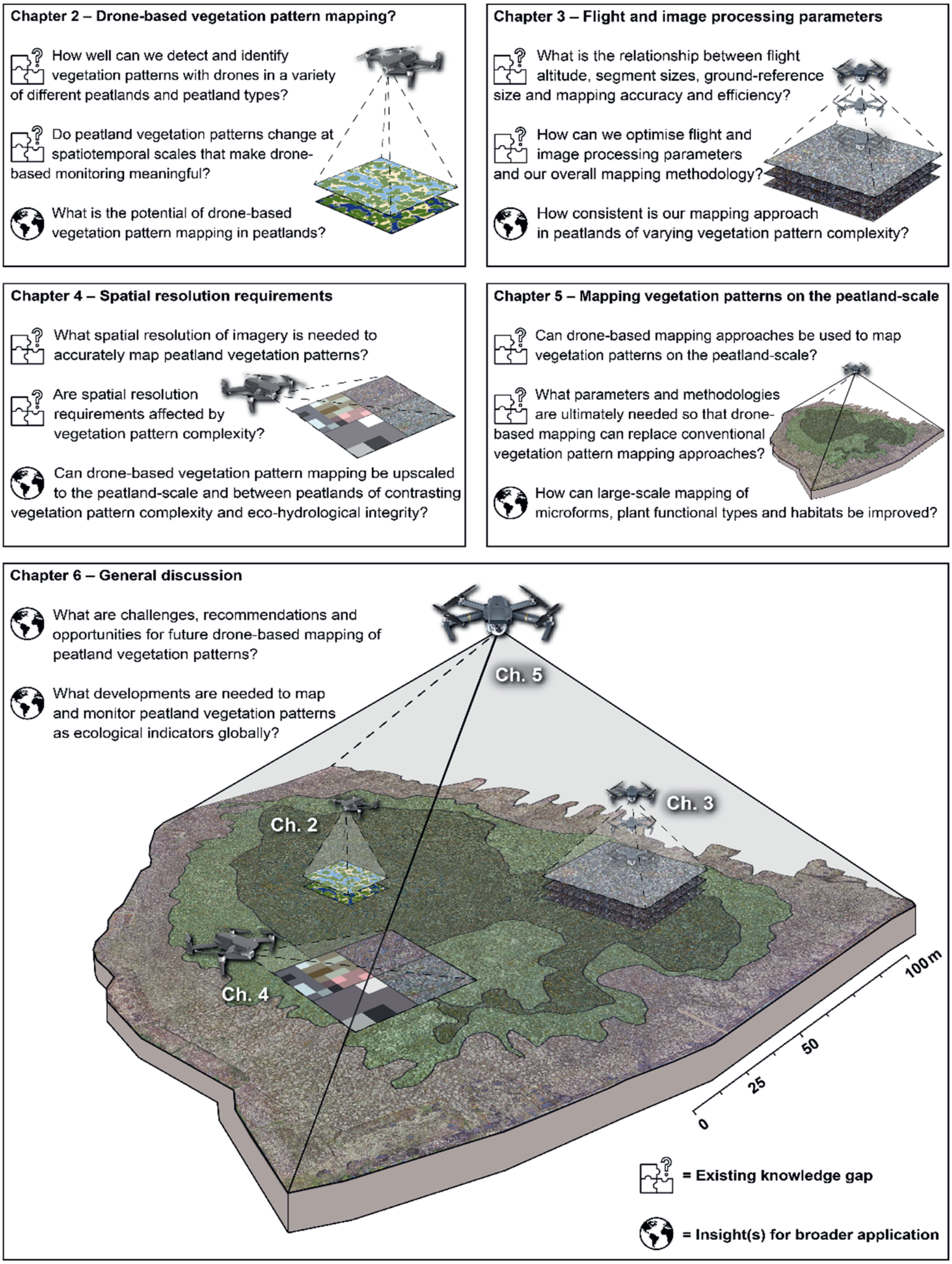
Chapter 2 of this thesis focuses on resurveying plots of fine-scale vegetation patterns in twelve of the studied peatlands that were previously manually mapped by Schouten (1984; Figure 1.6). We use this study as an opportunity to explore how well we can detect and identify peatland vegetation patterns using drone imagery in a variety of different peatlands and peatland types, and the potential of using machine learning classifications for vegetation pattern mapping in peatlands. Besides, this study also serves to improve our understanding of the spatiotemporal dynamics of peatland vegetation patterns over longer periods of up to 43 years. This information can be used to assess whether peatland vegetation patterns change at scales that make drone-based monitoring meaningful in the first place.

Chapter 3 describes the results of sensitivity analyses that we carried out in two of our peatlands with contrasting vegetation pattern complexity to assess the relationship between flight altitude (flight parameter), segment sizes (image processing parameter), ground-reference sample size (mapping methodology) and mapping accuracy and efficiency for plant functional types and microforms (Figure 1.6). On the one hand we use these results of this chapter to optimise flight and image processing parameters and our mapping methodology. On the other hand, we also use our findings to assess how consistent our mapping approach is in mapping peatland vegetation patterns of varying vegetation pattern complexity. Lastly, we explore minimum spatial resolution requirements through our defined minimum segment sizes.

Chapter 4 builds on the results of Chapter 2 and 3, and asks what spatial resolution of imagery is needed to accurately map peatland vegetation patterns (Figure 1.6). It also asks to what extent spatial resolution requirements are affected by vegetation pattern complexity (i.e. the spatial organisation of the vegetation patterns themselves). We therefore classify and map vegetation patterns in eight of our studied peatland that vary in their vegetation composition and vegetation pattern complexity through their eco-hydrological integrity. We also resample the spatial resolution of our drone imagery from source resolution to 1m to simulate spatial resolutions of imagery acquired from airborne and commercial satellites. Ultimately, the results of this study are used to determine upscaling potential of drone-based mapping to the peatland-scale by optimising computational efficiency and by understanding whether spatial resolution requirements are consistent over multiple peatlands of contrasting vegetation pattern complexity and eco-hydrological integrity.

Chapter 5 integrates the findings of Chapters 2, 3 and 4 to evaluate the potential of consumer-grade drones to accurately and efficiently map plant functional types, microforms and habitats on the peatland-scale (Figure 1.6). To test these expectations, we create classified maps of microforms and plant functional types for five of the raised bogs in our study area that range in size between 35–124ha and range in eco-hydrological integrity. We then classify habitats and develop maps using the proportions of microforms and plant functional types and range in microtopography, and compare them with conventional field-based ground-reference maps from the NPWS. Lastly, we also explore the spatial transferability of our habitat mapping approach between the studied peatlands. The results from this chapter can be used to understand what parameters and methodologies are ultimately needed so that drone-based remote sensing can replace conventional vegetation pattern mapping approaches. Besides, we use these findings to discuss how large-scale mapping of microforms, plant functional types and habitats can be improved.

Chapter 6 reflects on the main findings of this thesis and other recent studies to evaluate challenges, recommendations and opportunities for future drone-based mapping of peatland vegetation and their use as ecological indicators. I also cover upscaling of vegetation pattern mapping within and beyond the peatland-scale, and conclude with some remarks and statements on the future of peatland mapping based on the results of this thesis.



Chapter 2 – Drone-based vegetation pattern mapping?

🧩 How well can we detect and identify vegetation patterns with drones in a variety of different peatlands and peatland types?

🧩 Do peatland vegetation patterns change at spatiotemporal scales that make drone-based monitoring meaningful?

🌍 What is the potential of drone-based vegetation pattern mapping in peatlands?

Chapter 3 – Flight and image processing parameters

🧩 What is the relationship between flight altitude, segment sizes, ground-reference size and mapping accuracy and efficiency?

🧩 How can we optimise flight and image processing parameters and our overall mapping methodology?

🌍 How consistent is our mapping approach in peatlands of varying vegetation pattern complexity?

Chapter 4 – Spatial resolution requirements

🧩 What spatial resolution of imagery is needed to accurately map peatland vegetation patterns?

🧩 Are spatial resolution requirements affected by vegetation pattern complexity?

🌍 Can drone-based vegetation pattern mapping be upscaled to the peatland-scale and between peatlands of contrasting vegetation pattern complexity and eco-hydrological integrity?

Chapter 5 – Mapping vegetation patterns on the peatland-scale

🧩 Can drone-based mapping approaches be used to map vegetation patterns on the peatland-scale?

🧩 What parameters and methodologies are ultimately needed so that drone-based mapping can replace conventional vegetation pattern mapping approaches?

🌍 How can large-scale mapping of microforms, plant functional types and habitats be improved?

Chapter 6 – General discussion

🌍 What are challenges, recommendations and opportunities for future drone-based mapping of peatland vegetation patterns?

🌍 What developments are needed to map and monitor peatland vegetation patterns as ecological indicators globally?

🧩 = Existing knowledge gap

🌍 = Insight(s) for broader application

Figure 1.6 An overview of the individual chapters of this thesis, including three aims, questions and/or knowledge gaps of each research chapter, a visual overview of its content and a general overview of how all research chapters are connected to each other. All imagery in this figure is from Carrowbehy bog, Co. Roscommon, Ireland.

Chapter 2

There and back again: forty years of change in vegetation patterns in Irish peatlands

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Abstract

1. Northern peatlands play a disproportionally large role in the global carbon balance due to the massive amount of carbon stored in peat and ongoing sequestration. Vegetation composition and structure are recognised indicators for carbon sequestration and storage potential in these ecosystems, but decadal dynamics and roles of autogenic succession, climate, and land-use herein remain poorly understood.

2. We assessed vegetation changes in the least disturbed centre of twelve Irish peatland reserves sampled across a gradient in temperature and precipitation between 1978(1983)–2021, combining re-classified traditional high-resolution vegetation maps with recent very high-resolution drone imagery. Specifically, we tested whether microform proportions of open water, wet hollow, moist lawn, and dry hummock had changed and explored to what extent changes were related to climate and land-use drivers.

3. Results revealed that the studied peatlands underwent an overall unidirectional surface drying trend, with dry hummocks expanding at the expense of open water and wet hollow, while moist lawns remained approximately equal in proportions. The degree of change varied between the studied peatlands, with western blanket bogs and unrestored raised bogs experiencing more surface drying than mountain blanket bogs and raised bogs under hydrological restoration. While our results indicated climate and/or land-use as drivers of surface drying, our sample size was too small to make definitive conclusions about their exact role.

4. The overall change from wet to dry surface conditions between 1978–2021 occurred at a much faster rate than hitherto reported for these slow-changing ecosystems. This raises concern for the future resilience of peatlands to changes in climate and land-use, as well as their potential impact on the peatland carbon balance.

Keywords: peatlands, vegetation patterns, succession, surface drying, carbon sequestration, remote sensing

2.1 Introduction

Northern peatlands serve key ecosystem services for humans, like flood control, drinking water provision, water purification, recreation, biodiversity, and especially climate regulation through carbon These peatlands cover only 2% of the earths' surface (Xu et al., 2018), yet store between approximately 475–620Gt of soil carbon (Yu et al., 2010). This represents about 90% of the global peatland carbon pool (Yu, 2011), and more than one-third of all terrestrially stored soil carbon (Rydin & Jeglum, 2013). Given the disproportional size of this carbon stock, there is great interest in the response of peatland carbon to climate change and land-use changes in the 21st century. Understanding the rate in which peat-building vegetation responds to disturbances is necessary for accurate assessment of the future fate of peatland carbon stocks (Frolking et al., 2011; Loisel et al., 2021).

Peatland vegetation generally exhibits characteristic spatial patterns organised along small-scale topographic surface gradients called microforms (Rietkerk et al., 2004). Microforms range from relatively dry hummocks (peat surface up to ~50cm above the water table), to moist lawns, to wet hollows, to open water pools (peat surface always below the water table (Belyea & Baird, 2006). Hummocks are dominated by shrubs, lichen, graminoids, and more drought-adapted Sphagnum species, while hollows contain aquatic Sphagnum species interspersed with sedges (Andrus et al., 1983; Robroek, Limpens, Breeuwer, & Schouten, 2007; Rydin & McDonald, 1985), and open water pools generally contain no considerable amounts of vegetation. Lawns are typical transition zones between hummocks and hollows, and contain more intermediately drought-adapted Sphagnum species, occasionally interspersed with some shrubs, sedges, and forbs. Because of strong differences in productivity and decomposition between the plant functional groups associated with specific microforms (Aerts et al., 1999; Goud et al., 2017; Johnson & Damman, 1991; Laine et al., 2012; Turetsky et al., 2008), and because of the increasing ratio of methane to carbon-dioxide emissions through soil respiration along the water table gradient from hummock to hollow (Bubier et al., 1993; Krohn et al., 2017; Laine et al., 2007; Lunt et al., 2019; Waddington & Roulet, 1996), the spatial organisation of microforms in the landscape is a known indicator for carbon sequestration in peatlands (Couwenberg et al., 2011; Strack, Waddington, et al., 2006). Besides, retaining a diverse composition of plant communities through microform variations can not only directly increase the overall carbon sink function of a peatland (Robroek et al., 2017), but may also facilitate reorganisation through lateral expansion and contraction of microforms under changing environmental conditions (Belyea & Clymo, 2001). For example, peatlands with more equal proportions of dry and wet microforms are able to maintain carbon sequestration during both dry and wet years and can shift in microform proportions to accommodate multiple dry or wet years in a row. Consequently, the spatiotemporal dynamics of microforms and their associated vegetation are important because they have direct implications for both the short- and long-term carbon sink function of peatlands (Loisel & Yu, 2013).

It is thought that development and persistence of microforms are driven by eco-hydrological feedbacks between abiotic factors (i.e. pH, light availability, water table depth, nutrients, and temperature) and vegetation (Eppinga, Rietkerk, et al., 2009; Waddington et al., 2015). For instance, while Sphagnum facilitates its own perpetuation by creating recalcitrant, slowly permeable, and acidic litter that maintains high water tables and inhibits vascular plant growth (van Breemen, 1995), vascular plants promote their growth by drying and aerating peat soils through interception, transpiration, and nutrient accumulation through advective transport (Eppinga et al., 2008; Rietkerk et al., 2004). Microforms eventually develop when initial differences in peat characteristics and rates of peat accumulation resulting from the contrasting growth strategies of Sphagnum and vascular plants amplify over time. Under stable conditions, such as the flat central part of peatlands, microforms are best differentiated and can even form distinctive regular larger-scale patterns reflecting the dominant hydrological pathways (Eppinga et al., 2009). Furthermore, the extent and spatial organisation of microforms vary along environmental gradients. For example, wet microforms (open water, hollow, and lawn) generally dominate over dry microforms (hummock) under wet and cold conditions, while dry microforms (hummocks) may dominate under dry and warm conditions (Schouten, 1984). Consequently, microform variations may shift once environmental conditions systematically favour growth of species belonging to one microform over species of another (Belyea & Malmer, 2004; Dieleman et al., 2015; Wilson & Agnew, 1992).

Recent studies highlight that peatlands have started drying out substantially in the last centuries (Swindles et al., 2019; Zhang et al., 2022). Some other studies have also reported drying successional trends in disturbed and undisturbed raised bog sites in Europe and Canada over the last decades, and linked causes to either human disturbances, climate warming, or natural succession (e.g. Granlund et al., 2021; Gunnarsson et al., 2002; Kolari et al., 2021, 2022; Pasquet et al., 2015; Pedrotti et al., 2014; Pellerin et al., 2009; Pinceloup et al., 2020). Most of these studies have focused on individual sites or on changes in vegetation at plant species level, making upscaling of results difficult. In this study, we assess changes of larger scale vegetation patterns at the level of microforms (open water, wet hollow, moist lawn, and dry hummock) between 1978–1983 (hereafter referred to as 1978) and 2021 and explore to what extent changes can be ascribed to climate and land-use changes. We expected that: 1) changes in microform proportions are related to the location of a peatland along a climatological gradient of precipitation and temperature, and 2) changes in microform proportions are linked to the ecohydrological integrity of a peatland. To this end we sampled twelve Irish ombrotrophic peatlands across a gradient in temperature and precipitation between 1978–2021, combining re-classified traditional high-resolution vegetation maps with recent very high-resolution drone imagery.

2.2 Materials and methods

2.2.1 Study area

In Ireland, peatlands cover up to 21% of the landscape (Connolly, 2018), and occur across a broad climatological gradient of temperature, precipitation, and elevation. As a result, Ireland contains three major peatland types including raised bogs, mountain blanket bogs, and western type blanket bogs (Figure 2.1). Raised bogs developed in poorly drained depressions in central and eastern Ireland. On the other hand, blanket bogs, which occur under higher precipitation rates (usually >1200mm per year) and lower summer temperatures than the raised bogs are of two types: mountain blanket bogs in the uplands in different parts of the country, and lowland bogs along the west-coast.

In this study, we investigated twelve Irish peatlands, including six raised bogs, four western blanket bogs, and two mountain blanket bogs (Figure 2.1). Of all studied peatlands, ten are part of Irelands' Special Areas of Conservation (SAC's) network under the EU Habitats Directive (92/43/EEC), while two (Annaghbeg and Carbury) are part of Irelands' Natural Heritage Areas (NHA's; National Parks and Wildlife Service, 2018). This distinction is important, because only the four raised bog SAC's (Carrowbehy, Clara, Mongan and Raheenmore) have undergone hydrological restoration with drain blocking work (Fernandez et al., 2014; Table S2.2), starting as far back as 1984 on Mongan and continuing intermittently (e.g. restoration works on Clara and Raheenmore in 1994–96) on the four sites until recently, when all four were part of The Living Bog LIFE restoration project (LIFE14 NAT/IE/000032), which ran from 2016–2022. The blanket bogs included in this study have only been under active conservation since 2021 through the ‘Wild Atlantic Nature’ project (LIFE18 IPE/IE/000002).

All peatlands in the study area but Roundstone have been affected to a varying extent by anthropogenic disturbances in the direct vicinity (<2km), including domestic and commercial peat extraction, commercial forestry, drainage, and fire (Table S2.2). The landscape in the direct vicinity surrounding the studied peatlands also varies highly per location, but is predominantly composed of other peatlands, pastures, arable fields, coniferous forest plantations, and transitional woodland/heathland (Table S2.2). The peatlands are subject to a range in annual mean temperature between 9.0–11.8 ℃ (southwest to northeast) and precipitation between 936–1635 mm per year (northeast to southwest) with an elevation range of 21–497m above sea-level (Fick & Hijmans, 2017; Table S2.2). Climate has also changed within the peatlands over the studied period, with annual mean temperature increasing by approximately 1.6 ± 0.07 ℃ and summer precipitation decreasing by up to 5% between 1970–2000 and 2021 (Fick & Hijmans, 2017; Nolan et al., 2017; Table S2.2).

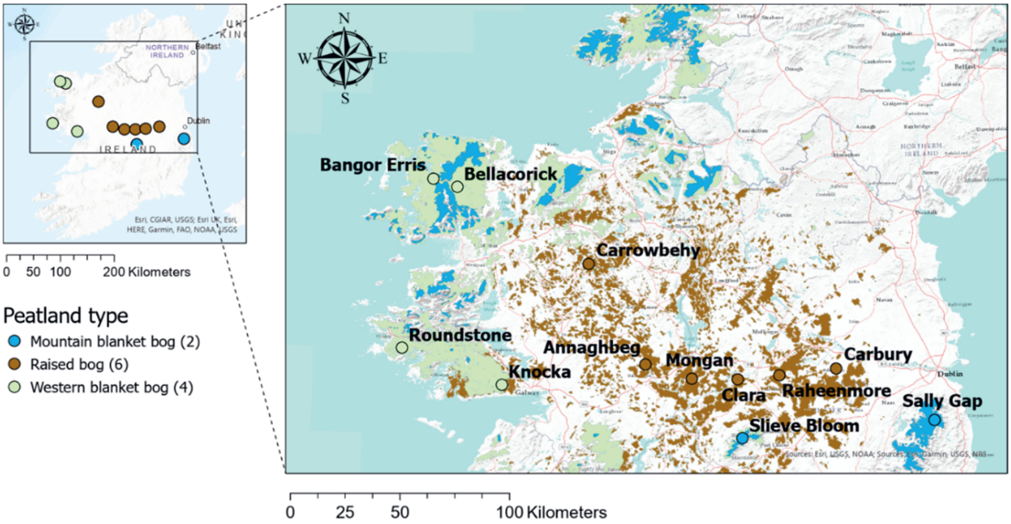


Figure 2.1 Study area showing the distribution of different peatland types throughout Ireland (Connolly & Holden, 2009), including the number of peatlands surveyed of that type in brackets: 1) mountain blanket bog (2), 2) raised bog (6), and 3) western blanket bog (4), and right) surveyed peatlands and their reference name. Survey locations are based on Schouten (1984).

2.2.2 Original vegetation survey

Between 1978–1983 a systematic study of the morphology and ecology of Irish ombrotrophic peatlands was performed (Schouten, 1984). Along climatic gradients (from east to west across the country and from lowland to mountain) 28 sites were selected, including fourteen raised bogs, four mountain blanket bogs, and ten western blanket bogs. Within all sites, transects were laid out from margin to the wettest sections of the peatlands (usually the centre), and along these transects the vegetation was sampled at two levels between August–September each year. First, the individual vegetation stands associated with the different microforms were sampled by means of Braun-Banquet relevés (after minimal sample plot sizes for the different stands had been determined by quantitative species-area curves through nested plot sampling from 1cm^2 to several m^2). The quantitative minimal area (i.e. the minimal plot size in which the species characteristic of the stand is represented in their characteristic cover/abundance degrees) varied for the different stand types (plant communities) between 0.5m^2 and 2.0m^2. The relevés collected in the study sites formed the basis for identification and classification of plant communities of Irish ombrotrophic peatlands (Schouten, 1990).

Microforms usually appeared in regular complexes which reflected the hydrological conditions in different sections of the peatlands. These complexes were directly related to surface inclination (Schouten, 2002), where level parts of raised bogs (usually the centre) as well as level sections of blanket bogs contained extensive areas with distinct microform gradients ranging from hummock to open water pools, while sloping marginal sections of raised bogs and slopes in blanket bogs had less distinct microtopography and usually contained only hummock and lawn. The characteristic complexes of these peatlands were manually mapped using m^2 grids where the different plant communities served as mapping units. At the level of these complexes a minimal plot size for mapping was also determined by a method comparable to the minimal area analysis for the relevés at the stand level. Here, quantitative species-area curves in nested plot series were extended to a much larger scale of often more than 100m^2, and the quantitative minimal area for the complexes – that is the minimal plot size in which all the characteristic plant communities of the complex were represented in their characteristic cover degree – varied between 10m^2 and several 100m^2 (Schouten, 1990). After the minimal plot size was determined for the characteristic complex of a peatland, full plots were set up along the transect using plot markers, annotated on the transect, and then manually mapped on its plant communities. During mapping, very small patches of plant communities contained by a larger plant community were assigned to the larger mapping unit rather than separately distinguished.

In total, sixteen maps were made of central community complexes in fifteen peatlands (with two separate plots mapped on Mongan), of which we used thirteen maps in twelve peatlands during this study because the other three maps were made in peatlands that have fully been destroyed during the study period (Table S2.1). In December 2020 we scanned all maps and imported them into ArcGIS Pro 2.8.2, after which we manually digitized each plot as a polygon feature so that we could calculate relative proportions of plant communities and their associated microforms in each mapped plot, which were used in assessing proportional changes between the original mapped plots and the newly retrieved classified microform maps.

2.2.3 Current vegetation survey

2.2.3.1 Locating original mapped plots

To investigate changes in peatland microforms, we revisited each of the twelve remaining surveyed peatlands in September 2021, and used information extracted from a combination of reconnaissance drone flights, shapes of open water pools, the original notes on the position of the historical plots along the original transects, local topography and remaining plot markers to pinpoint the exact locations of the historical plots (Figure 2.2). In total, we were able to locate again six of the thirteen plots from all twelve studied peatlands (Table S2.3). In the other seven cases where we could not find the original plot, we could only derive approximate locations using the following procedure: 1) we used the annotated historical transects to find the general peatland area used in the historical vegetation survey, 2) we defined new plots representative of the wettest locations in this area ranging between 50x50m and 100x100m. To assess if the larger spatial scale of observation affected the microform proportions, we compared classified microform proportions of the large new plot with the average microform proportions of five smaller plots with an area corresponding to the historical plots placed randomly within the new plot. We found that average microform proportions of total plot area between both approaches did not differ more than 2%. Based on these results, we assumed that new plots were representative to the size of the historical plots.

2.2.4 Drone imagery capture

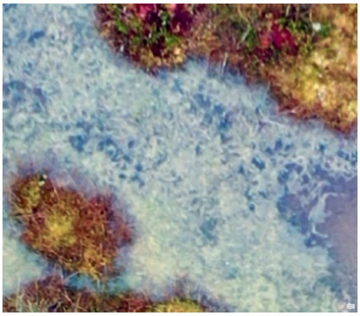
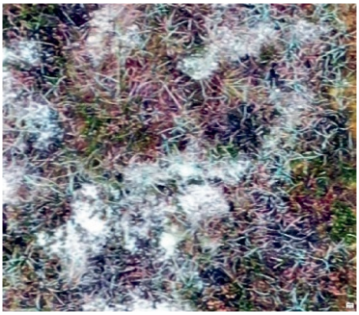
We collected drone images of all plots within the twelve peatlands between 7–21 September 2021 using a DJI Mavic 2 Pro drone with Hasselblad L1D-20c red-green-blue (RGB) colour sensor camera. We used the software DJI Ground Station Pro to design automated flights with 80% forward- and side-overlap at an altitude of 20–120m above ground (see Table S2.4 and also discussion section 4.2.2). Furthermore, we distributed four large 30x40cm checkerboard ground control points around the edges of a mapped plot and measured their position using a high-precision global positioning RTK-GNNS system (Topcon HiPer HR) and TopNET+ global navigation satellite system (GNSS) with 1–3cm accuracy to allow for georeferencing of the stitched drone images. We argue that four ground control points are sufficient for georeferencing of orthomosaics in our study because literature suggest using at least one ground control point per hectare or one ground control point per 100 drone images (Martínez-Carricondo et al., 2018; Oniga et al., 2018; Sanz-Ablanedo et al., 2018), while the flight areas of our study were always below one hectare (20x20m to 100x100m), and the maximum number of drone images taken within a peatland for use in orthomosaic stitching was 383 for Bangor Erris. Drone flights were conducted within one hour of solar noon under partially to fully cloudy conditions, where wind speeds during drone flights varied between days with low wind speeds to relatively high wind speeds of up to 28km/h. Besides, weather, and hydrological conditions during drone flights of 2021 were approximately similar compared to the original mapping in 1978, where precipitation over the course of summer 2021 was 94% normal (6% lower) with respect to previous decades (1981–2010), although annual temperature was on average 0.96℃ higher in 2021 than the 1961–1990 long-term average (The Irish Meteorological Service, 2022).

2.2.5 Ground reference data

After a drone flight was conducted for a specific peatland, we gathered ground reference data in a systematic way to make the best possible classification of the microforms per peatland plot rather than developing a widely applicable model for classifying microforms. This approach enabled us to best compare the historical maps mapped by hand with the new classified maps from drone imagery. In a first step, we went into the field with the principal investigator of the original vegetation survey to identify all microforms used in the historical survey. Here, we selected distinctive vegetation characteristics (relative position along microtopographical gradient, presence/absence of indicator species) to divide the four microform classes: 1) open water, 2) hollow, 3) lawn, and 4) hummock (Table 2.1; Schouten, 1984). In the second step we created a training/testing dataset for all microforms per peatland by marking microforms and indicator species of microforms in the field within the area covered by the drone flights and pinpointing their exact geographical location using our RTK-GNSS. The geographical locations of these point measurements were then linked to the values of the predictor variables within the computed segment by which they were contained to develop the final training/testing dataset (see also 2.2.6).

We adopted a targeted sampling approach for each plot because the cover of plant indicator species within each microform was highly variable, and this way we could ensure that less common plant indicator species of a specific microform were included in the training/testing samples for each plot. For each plot, we sampled all unique plant indicator species of all microforms at least 50 times (or by the number of occurrences if this was less than 50) while simultaneously considering the importance of area-proportional allocation of training/testing samples both within and between microform categories (Colditz, 2015). For instance, in a plot where hummocks contained *Cladonia portentosa* and *Sphagnum rubellum*, but were dominated by *Calluna vulgaris*, we allocated training/testing samples as 50/50/250 (350 total) for *Cladonia portentosa*, *Sphagnum rubellum,* and *Calluna vulgaris* respectively. In addition, we visually inspected the occurrence of all microforms within each plot to determine the area-proportional allocation of samples between microforms. For example, if hummock occurred in a ratio of approximately 2/1 with lawn, and we found that lawns contained three indicator species, we allocated a total of 175 training/testing samples (58 per indicator species) to lawn. In total, this resulted in between 162–561 test samples per peatland (Table S2.7).

Table 2.1 Overview of microform categories used for classification. Nomenclature for vascular plants is according to Stace (2019), while nomenclature for bryophytes is according to Blockeel et al. (2021).

Microform description	Example image
Open water Areas of open water with no considerable amounts of vegetation. Visible in drone images as blue, brown and black. Occasionally harbours aquatic species like: *Menyanthes trifoliata*, *Utricularia minor*, *Eriophorum angustifolium*	
Hollow Low-lying areas close to the water table, largely filled with semi-aquatic peat mosses, either floating or terrestrialised. Visible in drone images as bright green-to-darker green and grey Common species are *Sphagnum cuspidatum*, *Zygogonium spp.* (in dried out pools)	
Lawn Transition zones between hummock and hollow with mixed vegetation of peat mosses, some shrubs, sedges and forbs. Visible in drone imagery as red, yellow, brown and orange. Common species in raised bogs are *Sphagnum papillosum*, *Sphagnum medium*, *Narthecium ossifgragum*, *Rhynchospora alba*, *Erica tetralix*, *Eriophorum angustifolium*. In blanket bogs, additionally *Campylopus atrovirens*, *Campylopus brevipilus*	
Hummock More elevated areas mostly dominated by shrubs, hummock forming peat mosses, lichens and graminoids. Visible in drone images as purple, green, white, red, light blue, and grey. Common species are *Calluna vulgaris*, *Eriophorum vaginatum, Cladonia portentosa*, *Sphagnum rubellum*, *Racomitrium lanuginosum*, *Leucobryum glaucum*. In blanket bogs and western raised bogs also *Carex panicea*	

2.2.6 Drone imagery processing and deriving predictor variables

Before classifying microforms within each orthomosaic, we initially processed all drone-derived imagery products to create and derive the predictor variables that were used in classification. First, we used ortho-mapping software in ArcGIS Pro 2.8.2 to produce 1) a stitched RGB orthomosaic of each mapped plot, and 2) a high-resolution Digital Terrain Model (DTM; 5x pixel size of orthomosaic) for each orthomosaic using the photogrammetric data contained within each individual drone image (Table S2.3; Figure 2.2). More specifically, we created the DTM using extended terrain matching, which is a feature-based stereo matching technique for generating high density point clouds. We used both datasets for classification of microforms, where the RGB orthomosaic was used to determine spectral characteristics, and the DTM was used for derivation of topographical characteristics. Second, we grouped all pixels in a stitched orthomosaic into segments (objects) using a mean-shift clustering algorithm based on similarity in spectral values and spatial characteristics of the orthomosaic (Figure 2.2). We used a preliminary classification for one plot to define a minimum segment size of $56cm^2$ (7.5x7.5cm) so we could distinguish small and clustered features within the drone imagery. Afterwards, we computed three shape metrics for each segment to quantify their spatial characteristics (Table S2.4). Third, we detrended each DTM by fitting a second-order polynomial function through the elevation points in the DTM, and subsequently subtracting the DTM from the fitted trend function (Figure 2.2). We did this because the DTM of each orthomosaic showed a slight dome shaped elevational trend from the centre to the edges of the images (representing the slope from centre to edges of the bog). Thus, this detrended DTM represents relative microtopographical differences in the landscape more realistically. Lastly, we calculated several RGB-derived vegetation colour indices as additional predictor variables for each segment in an orthomosaic (Table S2.4; Figure 2.2), because these may emphasise spectral differences between vegetation and aid in improving classification of microforms. For instance, when using only RGB values as predictor variables, dark colours tend to be more spectrally similar to other dark colours than the same colour with different brightness. However, using Hue, pixels with the same colour are spectrally similar regardless of their brightness, diminishing the potential effect of shade in incorrectly determining vegetation boundaries.

2.2.7 Microform classification

In total, we used 25 predictor variables in the classification of microforms, consisting of the mean and standard deviation of RGB values, mean of hue-saturation-value colour model values, ten vegetation colour indices (variables combining two or more bands), elevation (minimum, maximum, and mean of DTM) and shape metrics (pixel count, rectangularity, and compactness), computed for each segment in the orthomosaic (Table S2.4). We classified plots using the training/testing samples of each plot in combination with the ensemble classifier Random Forest (Breiman, 2001) in Python's Scikit-learn module (Pedregosa et al., 2011) with the 25 predictor variables as input. Random Forest has proven to be a robust machine learning algorithm for remote sensing data with little demand on computing power (Belgiu & Drăguţ, 2016; Rodriguez-Galiano et al., 2012), as well as having high interpretability. To fit the Random Forest models, we resampled the training/testing samples of each plot using stratified K-fold cross-validation with a ratio of 80:20 for training versus testing (analogous to 5-folds) because it minimized variance of cross-validation model accuracy in our study (Jiang & Wang, 2017; Figure 2.2). Hyperparameters of the Random Forest models were kept at default values as accuracy improvements through hyperparameter tuning were negligible (<1%).

We computed classification accuracy metrics for each classification by averaging precision, recall, and F1-score (as calculated from the relative number of true positives, true negatives, false positives, and false negatives in the confusion matrix) over all folds in the Random Forest models using the testing samples (Figure 2.2). Here, an average value of 1 indicates a perfect prediction, where any value in between 0–1 (or 0–100%) expresses the probability that a testing sample is correctly classified. All segments in an orthomosaic were classified by taking the most frequently classified microform for each segment over all folds. We then retrieved an overall ranking of variable importance for each classified image by computing the Gini importance, which we used as it is a commonly used measure for variable importance in peatland studies (Behnamian et al., 2017; Millard & Richardson, 2015). Because variable importance rankings for each plot varied between Random Forest model runs (i.e. folds), we averaged Gini importance over all folds to receive more stable mean importance values for each classification (Behnamian et al., 2017). Lastly, we finalized a classified image by applying post-classification smoothing where we merged all classified segments smaller than $0.09m^2$ (minimum segment size*4^2) with neighbouring segments sharing the longest border (Figure 2.2). This merging procedure mimics the traditional vegetation mapping methodology, where very small patches with plant communities of one microform within another larger microform were assigned to the larger class rather than separately distinguished.

2.2.8 Statistical analyses

To analyse whether microform distribution changed between 1978–2021, we calculated the relative contribution of each microform to the plot area (i.e. microform proportions) for both the original plots and the newly classified images (Figure 2.2). We then compared the differences in microform proportions between both years for all peatlands by applying *t* tests or Wilcoxon rank tests, depending on whether assumptions of normality were met. In addition, we also calculated a ‘net drying’ value for each peatland by calculating the net shift towards drier microforms. This allowed us to compare total proportional microform changes among peatlands, where a positive value indicates a net transition towards drier microforms, and a negative value indicates a net transition towards wetter microforms. For instance, if the proportions of open water, hollow, and lawn in a peatland each decreased by 10%, the sum of the equation would total -30%, yielding a net drying value of 30% through the decline of wetter microforms at the expense of the dry microform (hummock). However, if not only open water and hollow, but also hummock declined by 10%, the loss of wetter microforms (open water and hollow to lawn) is offset by a gain of wetter microforms (hummock to lawn). In such a case, the net drying value would be 10%. We also evaluated the effect of peatland type and restoration status on the extent of change by grouping net drying values per peatland type (Figure 2.1), and further separating raised bogs by their restoration status (hydrologically restored special areas of conservation vs non-restored natural heritage areas). Although the number of sampled peatlands was too low to perform meaningful mean difference tests between these groups, it offered the ability to evaluate and interpret the potential role of different groups on changes in microform proportions (Figure 2.2).

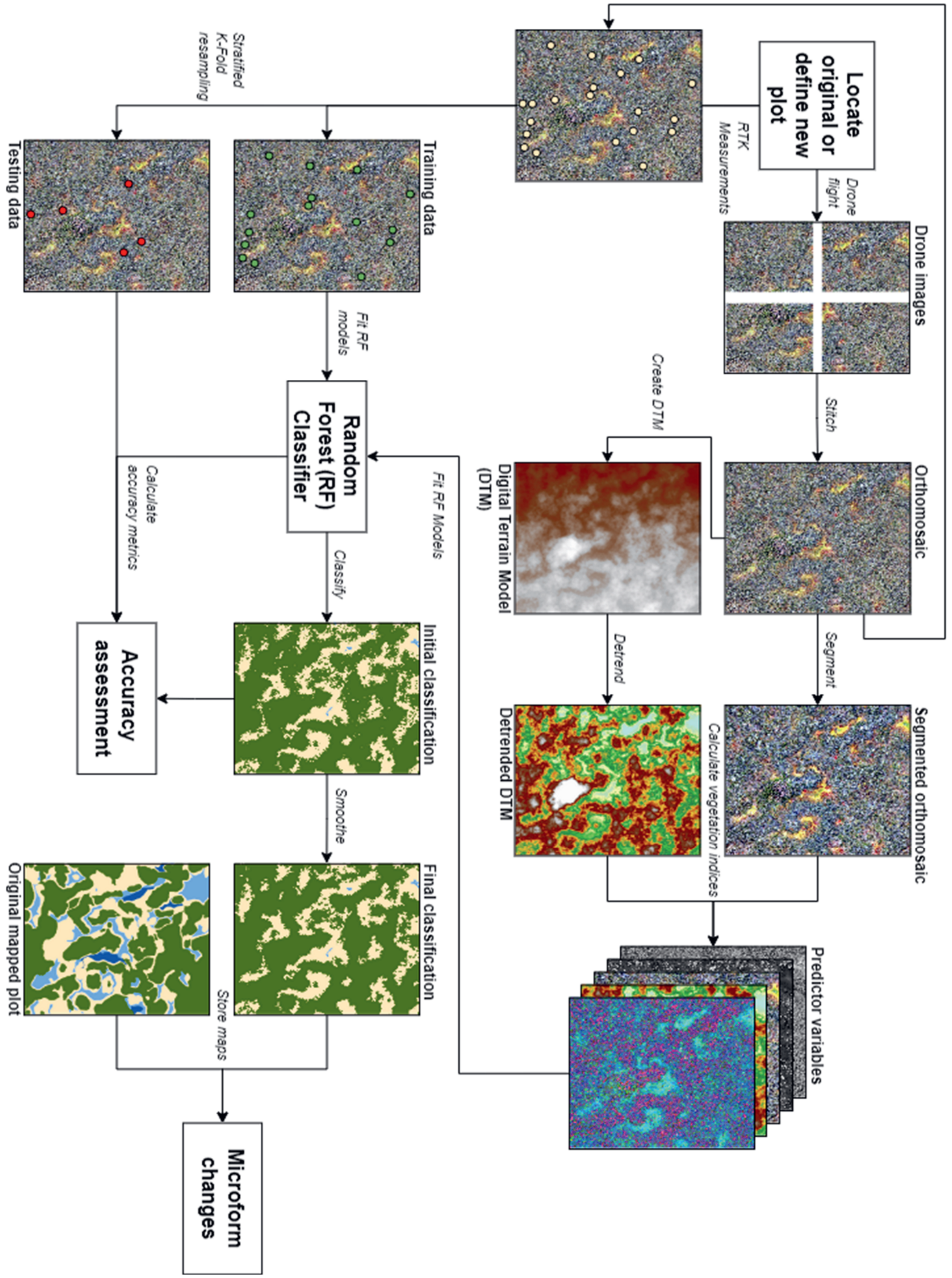


Figure 2.2 Schematic representation of the workflow used for assessing changes in microform proportions in the study on Irish peatlands. Visualized are processes (white boxes) and raster datasets (images) used for classification of microforms for each mapped plot. Images are snippets from Mongan.

2.3 Results

2.3.1 Classification accuracy

We classified microforms for a total of thirteen images distributed over the twelve peatlands (Table S2.6; Figure S2.1–S2.13; see also Figure 2.4), where each peatland had one image and Mongan had two images. Accuracy of classified images was well over 90% on average (Table S2.6), ranging from 86.2% for Sally Gap to 98.2% for Roundstone. Classification accuracy of Sally Gap was likely lowest because the image was slightly overexposed, and hummock and lawn were harder to distinguish as a result of the lower contrast. Classification accuracies per microform were also generally very high, with accuracies reaching at least 90% in near all cases (Table S2.6). Misclassifications most often occurred between lawn and hummock (Table S2.8), and while small misclassifications between lawn and hummock may affect net drying values, the often near equal proportions by which these microforms were misclassified as one another likely negate at least part of their effect (Table S2.8). Analysis of variable importance over all thirteen classified images indicated that elevation, vegetation colour indices, and hue-saturation-value colour model values were among the most important predictor variables in classification of microforms, whereas RGB values and shape indices of segments were hardly ever of importance in the Random Forest models (Figure S2.14). Besides, in classification of most images that still have a well-defined microtopography, elevation (min, max, and mean), as well as Hue, were often in the top five most important predictor variables (Table S2.7; Figure S2.14). This highlights their key role as predictor variables in determining microform distribution, as well as emphasizing the added value of a drone derived DTM as a predictor variable in classifying peatland microforms.

2.3.2 Microform changes

Between 1978–2021, the proportions of peatland microforms changed significantly, shifting away from wet microforms towards drier microforms (see also Figure 2.4). Averaged over all thirteen classified images, open water (from 8.30% to 3.66%) and hollow (from 18.80% to 8.22%) experienced a statistically significant decrease, whereas hummock (37.76% to 61.92%) displayed a strong statistically significant increase (Figure 2.3). Although lawn decreased (35.14% to 26.20%), it did not show statistically significant changes over time (Figure 2.3), which is caused by the small relative decrease between 1978–2021 as opposed to other microforms in combination with high variance within the microform proportions of the class in both years. Overall, these results suggest a unidirectional surface drying trend. It further became clear that changes in microform proportions differed highly between peatlands (Table 2.2), with the highest rate of net drying being 66% (Annaghbeg), while net drying in Slieve Bloom equalled -5%, which indicates that wetter microforms have expanded at the expense of drier microforms. Net drying also differed between peatland types and restoration status (Figure 2.5). For instance, despite having a similar baseline situation with high proportions of wet microforms in 1978 (Figure S2.1–Figure S2.13), hydrologically restored raised bogs (SAC's) experienced less drying on average (16%, n = 5) than non-restored raised bogs (NHA's; 51%, n = 2). Besides, western blanket bogs experienced high average net drying (38%, n = 4) while mountain blanket bogs experienced lowest average net drying (5%, n = 2). Although sample sizes per peatland type were low, and we refrained from performing statistical tests on this data, these results suggest that the differences in microform changes may be associated with peatland type and restoration efforts. Mountain blanket bogs are located in a colder and wetter climate than other peatlands in the study area, while raised bog SAC's are the only peatland type that have undergone active restoration measures. Consequently, these peatland types have potentially remained more resistant to changes in microform proportions than others because of preserved or reinstated surface wetness during the study period. This pattern highlights a complex set of drivers potentially affecting microform changes.

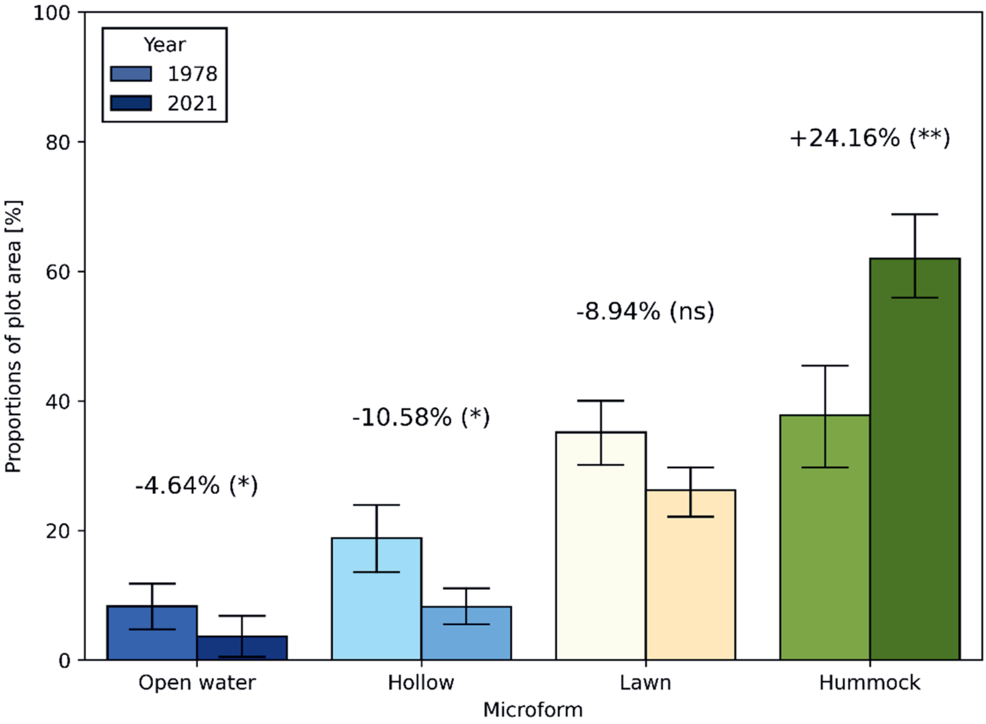


Figure 2.3 Bar plots summarizing percentual changes in microform proportions of the total plot area between mapped plots (1978) and classified images (2021) across all peatlands (*n* = 13) in the study area. Error bars represent standard errors (SE), and statistical results represent mean difference tests. Open water (W = 1, p = 0.011), Hollow (W = 6, p = 0.009), Lawn (t = 1.57, p = 0.143), Hummock (t = -4.63, p < 0.001). * Indicates a statistically significant difference (p < 0.05), and ** indicates a statistically significant difference (p < 0.001) for each microform between 1978 and 2021. “ns” means not statistically different.

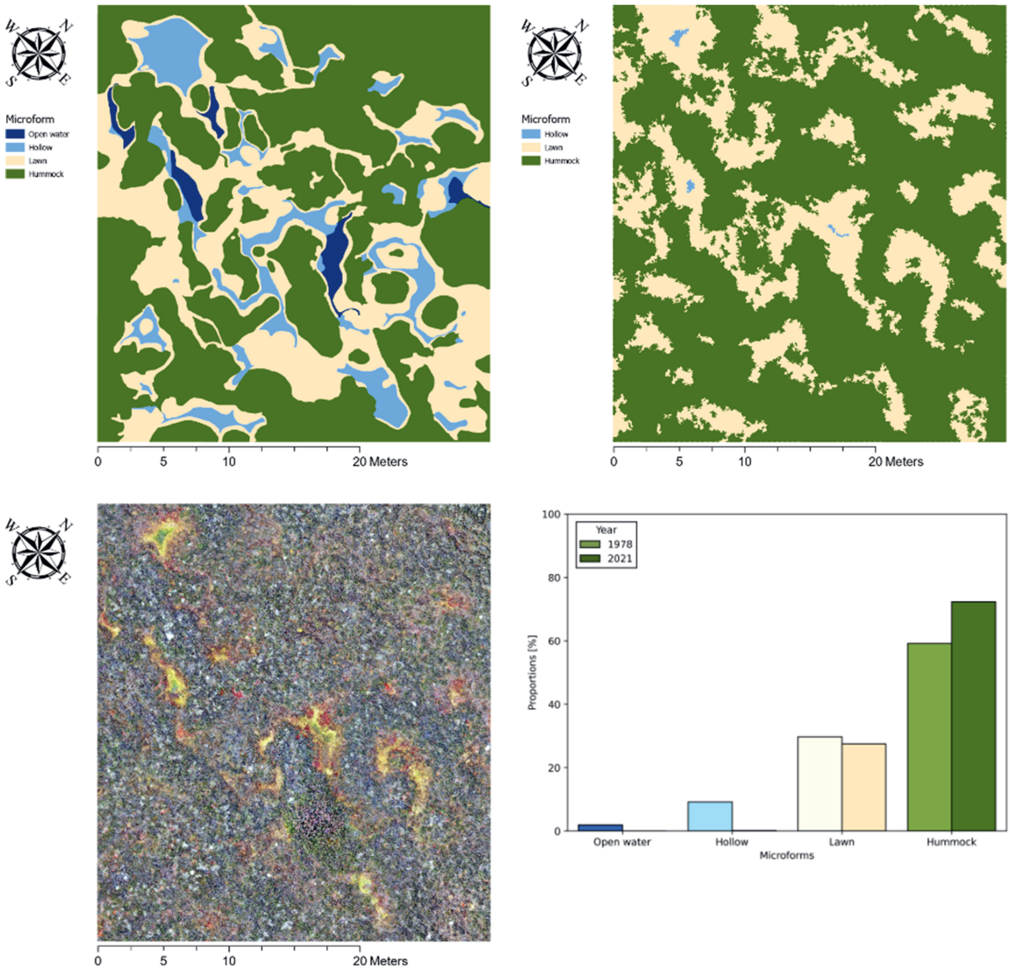


Figure 2.4 Overview of microform changes in Mongan between 1978–2021. Represented are the original mapped plot from 1978 (top left), the newly classified map from 2021 (top right), the orthomosaic from drone imagery at 20m altitude (bottom left) and a bar graph highlighting the changes in microforms proportions of the total plot area between the original mapped plot (1978) and the newly classified map (2021; bottom right).

Table 2.2 Overview of net drying and changes in microform proportions of plot area (%) for each peatland. Represented are the specific peatland, their peatland type: raised bog (RB), western blanket bog (WBB), and mountain blanket bog (MBB), as well as net drying and microform proportions of plot area (%) for open water, hollow, lawn and hummock microforms for each peatland. Peatlands are sorted from highest to lowest net drying. Colours indicate extremity of net drying and changes in microform proportions of plot area, where black colours highlight 0–10% change, orange highlights 10–20% change and red highlights >20% change.

Peatland	**Type**	**Net drying [%]**	**Open water**		**Hollow**		**Lawn**		**Hummock**	
			1978	**2021**	**1978**	**2021**	**1978**	**2021**	**1978**	**2021**
Annaghbeg	RB	66	0	0	2	0	79	15	19	85
Bangor Erris	WBB	50	2	2	40	19	48	19	10	60
Roundstone	WBB	42	2	0	61	21	32	48	5	31
Carbury	RB	36	1	0	9	0	29	3	61	97
Bellacorick	WBB	34	0	0	36	2	51	53	13	46
Knocka	WBB	26	23	4	11	10	52	45	15	41
Carrowbehy	RB	19	17	0	11	18	24	16	47	66
Clara	RB	19	0	0	44	26	35	38	21	37
Mongan 2	RB	18	16	0	13	11	17	24	54	66
Sally Gap	MBB	14	45	41	1	1	38	28	17	30
Mongan	RB	13	2	0	9	0	30	28	59	72
Raheenmore	RB	9	1	0	6	0	18	15	76	85
Slieve Bloom	MBB	-5	0	0	0	0	5	11	95	89

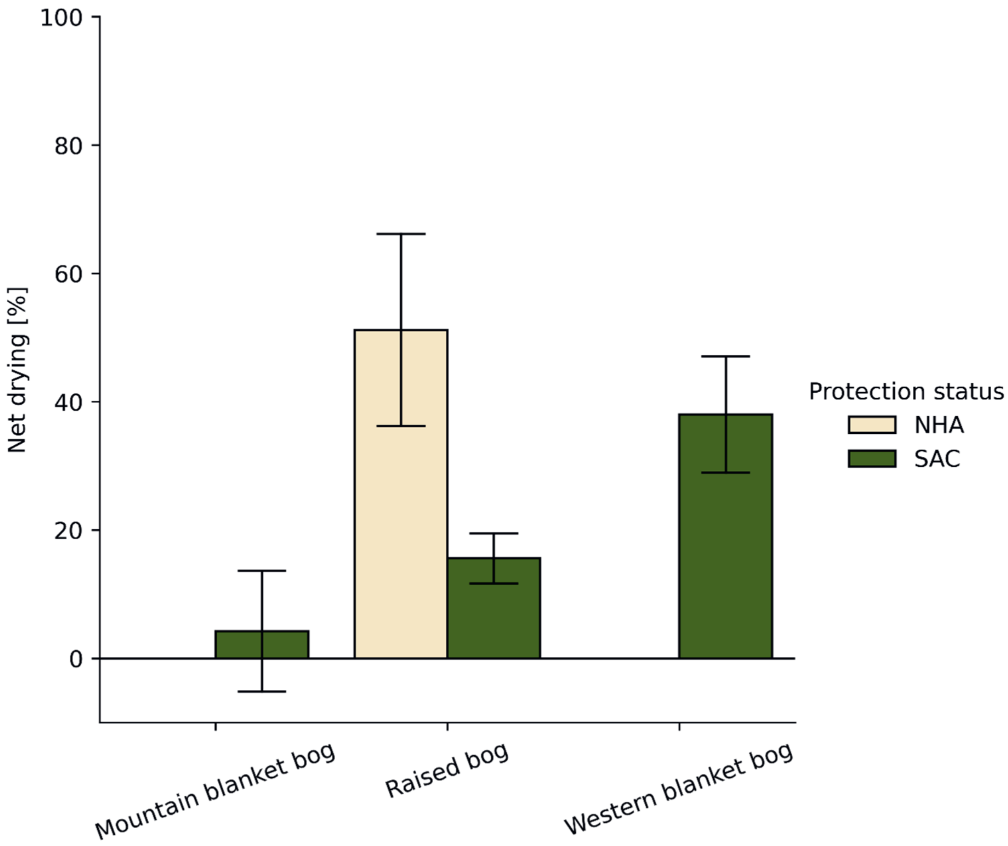


Figure 2.5 Bar plots summarizing average net drying values over all peatlands and peatland types in the study area as measured by an increase in proportions of drier microforms between original mapped plot and newly classified image. Peatland types are raised bog NHA (*n* = 2), raised bog SAC (*n* = 5), western blanket bog SAC (*n* = 4), and mountain blanket bog SAC (*n* = 2).

2.4 Discussion

2.4.1 Microform dynamics over a 40-year time-period

We found that peatlands in our study have undergone significant changes in microform proportions between 1978–2021, with dry microforms (hummock) expanding at the expense of wet microforms (open water and hollow), and proportion of lawns remaining approximately equal. Overall, this suggests that peatlands in our study have undergone a unidirectional successional surface drying trend during the study period. This is interesting, because while peatland microforms have historically shown to be resilient to gradual, long-term changes in climate and hydrology (Dise, 2009; Lamentowicz et al., 2019; Nungesser, 2003; Page & Baird, 2016), they have shown to respond rapidly to profound short-term anthropogenic disturbances like nitrogen loading (Bubier et al., 2007; Limpens et al., 2011), drainage (Breeuwer et al., 2009; Harris et al., 2020; Talbot et al., 2010), and drought induced peat fire (Kettridge et al., 2015; Nelson et al., 2021; Turetsky et al., 2015). Peatland microforms may thus exhibit non-linear behaviour, where long periods of stability under gradual long-term climatic changes can be punctuated by rapid changes when destabilizing effects are so substantial that they overrule the internal self-regulating capacity of microforms.

2.4.2 Degradation of Irish peatlands

In Ireland specifically, nearly all peatlands have been impacted by anthropogenic disturbances during their history (Malone & O’Connell, 2009). Activities like domestic and commercial peat extraction, overgrazing, drainage, commercial forestry, wind farms, and wildfires have all compromised the hydrological integrity of many of Irelands’ peatlands (National Parks and Wildlife Service, 2018; Wilson et al., 2013; Table S2.2; Table S2.10). Although many of these activities initially occurred on the peatland margins, their impact (particularly that of drainage) can extend well beyond the margin, potentially resulting in cracks, subsidence, deformation, and collapse throughout the whole peatland (National Parks and Wildlife Service, 2018; Schouten, 2002; van der Schaaf, 2002). This is because the lowered water table brought about from drainage can result in enhanced oxidation and changes to the peat properties, which in turn can result in changes to their hydraulic properties (Price, 2003). Examples of these drainage impacts have been studied comprehensively at one of our study sites (Clara), where Regan et al. (2019) recorded subsidence impacts 900m from the bog edge as a result of marginal drainage over a 28-year period. Considering all mapped plots in this study were situated in the wettest and most central areas of a peatland, the fact that even most of these areas have experienced notable surface drying between 1978–2021 suggests that peatlands in our study have likely lost at least part of their resilience. Here, prolonged environmental stress has overruled the internal self-regulating mechanisms of microforms, causing their vegetation to start shifting. These peatlands may continue to move away from wet peat-forming conditions towards dry conditions where shrubs start to dominate unless extensive restoration and rewetting measures are undertaken that re-establish a *Sphagnum* cover large enough to reinstate the self-regulating mechanisms that enable and sustain peat-formation (Crowley et al., 2021; Renou-Wilson et al., 2019; Rochefort, 2000; Tuittila et al., 2000; Wilson et al., 2013). Pouliot, Rochefort, and Karofeld (2011) found that if such restoration activities are carried out correctly, microforms comparable to natural peatlands can form again within 10–30 years.

2.4.3 Effect of peatland type, climate, and restoration on variability in microform changes

Changes in microform proportions varied remarkably between peatland types and restoration status (Figure 2.5), and sometimes even within peatland types (Table 2.2). For instance, western blanket bogs experienced the highest net drying of all peatland types in the study area. While we can likely attribute some of this drying to afforestation, drainage or peat cutting that occurred in the direct vicinity of most of these peatlands (Table S2.2; Table S2.10), the fact that Roundstone experienced considerable surface drying while being located more than 2km from any human disturbance is particularly noteworthy. Climate change could potentially play a role in this, as it has affected both temperature and precipitation in the whole of Ireland in the last decades (Nolan et al., 2017; Nolan & Flanagan, 2020), while Roundstone already experienced the highest annual mean temperatures of all peatlands in the study area. It is therefore possible that these peatlands have fallen or are starting to fall outside the climate envelope for optimal growth of Sphagnum species (Gallego-Sala et al., 2010; Gallego-Sala & Colin Prentice, 2013). Besides, Roundstone is hydrologically connected to its larger environment via groundwater flow, as illustrated by the presence of vegetation with more minerotrophic characteristics. This partial dependency on a larger scale hydrological system may have made the peatland more sensitive to climate and land-use changes further away. Also, changes in hydrological conditions would be particularly impactful in blanket bogs compared to raised bogs because the former have lower hydrological self-regulating capacity resulting from lower Sphagnum cover and thinner acrotelm depth (Rydin & Jeglum, 2013). Furthermore, we also saw low net drying of the two mountain blanket bogs in our study (Table 2.2). Because these peatlands were characterized by 1.4–2.8℃ cooler mean annual temperature, 3.3–4.2℃ cooler wettest quarter and 186–386mm higher mean annual precipitation than other peatlands in our study, their position within a colder and wetter mountain climate may have buffered the effect of climate change on their vegetation dynamics up until now (Morelli et al., 2016; Stralberg et al., 2020). Observed net drying within these peatlands could therefore likely be attributed to the moderate afforestation (Slieve Bloom) and peat-cutting (Sally Gap) in their near surroundings since 1978 (Table S2.2; Table S2.10).

In addition to mountain blanket bogs, raised bog SAC's also experienced relatively low net drying as opposed to raised bog NHA's and western blanket bogs (Figure 2.5). It seems likely to assume that the limited surface drying of the raised bog SAC's is related to three main factors. First, peatland sites chosen as SAC's in the 1990's had a better baseline condition than those later recognised as NHA's (National Parks and Wildlife Service, 2018), and this better condition may itself have offered them some protection or enhanced resilience against environmental change. Adding to this is that raised bog SAC's in our study are generally large peatlands and so a plot in the central part tends to be much further from the margins (and its drainage impacts) than one in the centre of an NHA. Second, raised bog SAC's are the peatlands where peat cutting and drainage works were first curtailed or ceased before any other Irish peatland types, which could have prevented further microform succession by reinstating surface wetness (Crowley et al., 2021; Renou-Wilson et al., 2019). Lastly, raised bog SAC's are the only peatlands in our study that have undergone extensive restoration and rewetting work in the last decades (Mackin et al., 2017; National Parks and Wildlife Service, 2018; Table S2.2), and therefore have a stronger restoration status. Nevertheless, our computed net drying values show that all of the raised bog SAC's in the study area have undergone net drying despite having received hydrological restoration, indicating that these interventions have not fully restored the peatland water balance, but only alleviated surface drying as opposed to non-restored peatlands.

All in all, causes for the observed variations in surface drying in our study remain complex, but likely result from an interplay of destabilizing effects (climate change and human disturbances) and stabilizing effects (restoration and location along the climate gradient), as well as the inherent characteristics and historical integrity of a peatland. To elucidate the main drivers of ecological changes in these peatlands, one would need to systematically quantify the destabilizing effects (e.g. length of drainage ditches, time since drainage), stabilizing effects (e.g. extent of restoration, time since restoration), and relevant peatland characteristics (e.g. peatland size, distance of plot to edge of peatland), and assess their relationship with net drying over a larger sample of peatlands than available in our study.

2.4.4 Differences between the original and current mapping methodology

It has to be noted that the computed net drying values for each of the plots may have been affected by differences in mapping methodology between the original vegetation survey (manual mapping) and current vegetation survey (drone-derived image classifications). However, we strove to minimize this effect by 1) aligning the characteristics of mapped units (microforms) in the original vegetation survey with those that would be visible from drone imagery in the field together with the principal investigator of the original survey, and 2) by applying a post-classification smoothing to remove the salt-and-pepper effect that results from classification to align better with the minimum mapping unit and mapping methodology of the original survey. While this resulted in mapping units with approximately the same size or order of magnitude for both methodologies, we did notice that patch sizes for all mapping units are substantially smaller or larger in some plots (Table S2.5). Nevertheless, it is difficult to deduce to what extent these differences are actually caused by differences in mapping methodology, or whether changes in patch sizes within mapping units are caused by vegetational changes between 1978–2021. For instance, homogenisation of the vegetation resulting from an increase in hummock may increase patch sizes for hummock while breaking up patches of microforms that are decreasing in extent (i.e. open water, hollow, and lawn), hereby affecting the values of their patch metrics. Although differences in patch metrics between mapping methodologies are likely a combination of both causes, we believe they have no noteworthy effect on the observed surface drying trend in microform proportions in our study, especially given the near full loss of major wet microforms (open water, hollow) in some peatlands, which is independent of such patch metrics.

2.5 The use of drone imagery in classification of peatland vegetation patterns

2.5.1 Reasons for the high accuracy of microform classifications

Multiple recent studies have highlighted that the use of drone imagery is a promising method for classification and quantification of vegetation patterns in peatlands (e.g. Beyer et al., 2019; Bhatnagar et al., 2020; Lehmann et al., 2016; Palace et al., 2018; Räsänen et al., 2019, 2020). Our results support these findings, with high accuracies (>90%) of microform classifications in all but one image. The high observed accuracy of drone imagery classifications in our study may be attributed to three reasons. First, the spectral reflectance of dominant peatland plant functional types and their associated position along the microtopographical gradient differs markedly among each other (Bubier et al., 1997; Harris & Bryant, 2009; McPartland et al., 2019). As a result, vegetation in peatlands is inherently suitable for remote sensing classification, and its success can be improved further by adequate categorization of vegetation classes. Second, the ultra-high resolution by which drone imagery can capture the fine-scaled, heterogeneous nature of peatland vegetation is a major advantage over satellite approaches, which currently fail to provide adequate spatial resolution for determining the distribution of individual species or vegetation types like plant functional types and microforms. Drone imagery is thus especially useful here because image segmentation can be used to optimize the distinguishability of microforms if the spectral properties of individual species or plant functional types belonging to a certain microform become aggregated to a specific signature. Third and lastly, our combined use of spectral with topographical data is particularly advantageous for the classification of peatland vegetation because the distribution of vegetation and their associated microforms are so closely related to the water level. Consequently, drone derived DTM's are highly effective in peatlands (Harris & Baird, 2019; Moore et al., 2019; Räsänen et al., 2020), not only because they can capture the microtopographical differences in the landscape at an ultra-high resolution, but also because peatlands are often relatively flat and tree-less, which improves accuracy of photogrammetric elevation products (Czapiewski, 2022; Lovitt et al., 2017). These factors highlight that drone-based image classifications are a highly suitable, efficient, and flexible method for mapping fine-scale variation and dynamics in peatland vegetation (and thus microforms). We argue this method should be explored further, because it characterizes peatland vegetation patterns at scales that most realistically and accurately reflect their fine-scale heterogeneous nature. This way, it can potentially serve to bridge the current gap between traditional mapping approaches (e.g. transect or quadrat methods) and satellite remote sensing measurements.

2.5.2 Recommendations for further improvements of mapping peatland vegetation patterns

While the use of drone imagery for classification of microforms in this study already showed strong potential, we believe that both the classification accuracy and/or the efficiency of our process can be optimised in several ways. For instance, classification accuracy in our study has shown to be robust against increasing flight altitudes from 20m to 120m (Table S2.3; Table S2.6). Although this effect must be investigated for more peatlands and multiple altitudes, it already shows that when flying at 120m (maximum flight altitude in the European Union), microforms are still highly distinguishable, and perhaps even more logically separated because the spectral properties of small patches of individual plants and vegetation types associated with a specific microform could more accurately become aggregated to the microform level than at 20m. This also makes it worthwhile to further investigate optimal segmentation scales (i.e. minimum segment size) that reflect the real patchiness of microforms to improve classification accuracy and the role of shape metrics as predictor variables in classification (Dronova et al., 2012; Räsänen & Virtanen, 2019). Performing the same analysis on a higher altitude would also improve upscaling capabilities by dramatically reducing both flight time per area and computer processing time. Consequently, smaller area images at 20m could henceforth be used for construction and validation of training data (especially if peatlands are hard to access), while images at 120m could be retrieved for classification (Räsänen et al., 2019; Räsänen & Virtanen, 2019). Furthermore, performing feature selection by keeping only the most important, ecologically relevant, and uncorrelated variables can increase classification accuracy while simultaneously reduce model complexity (e.g. Georganos et al., 2018; Millard & Richardson, 2013; Räsänen et al., 2014; Timm & McGarigal, 2012), and may be required in the future where predictor variables seem superfluous. Lastly, because classification accuracy of Random Forest models can be sensitive to training sample size, class imbalances within training samples, and spatial autocorrelation between samples (Belgiu & Drăguţ, 2016; Dalponte et al., 2013; Millard & Richardson, 2015), it is important to consider these factors in the development of a sampling strategy to prevent optimistic classification results. While we aimed to sufficiently consider these factors in our sampling strategy, a fully random strategy will minimize their effect, although then care must be taken that uncommon microforms (or uncommon indicator species within microforms) are also sampled adequately.

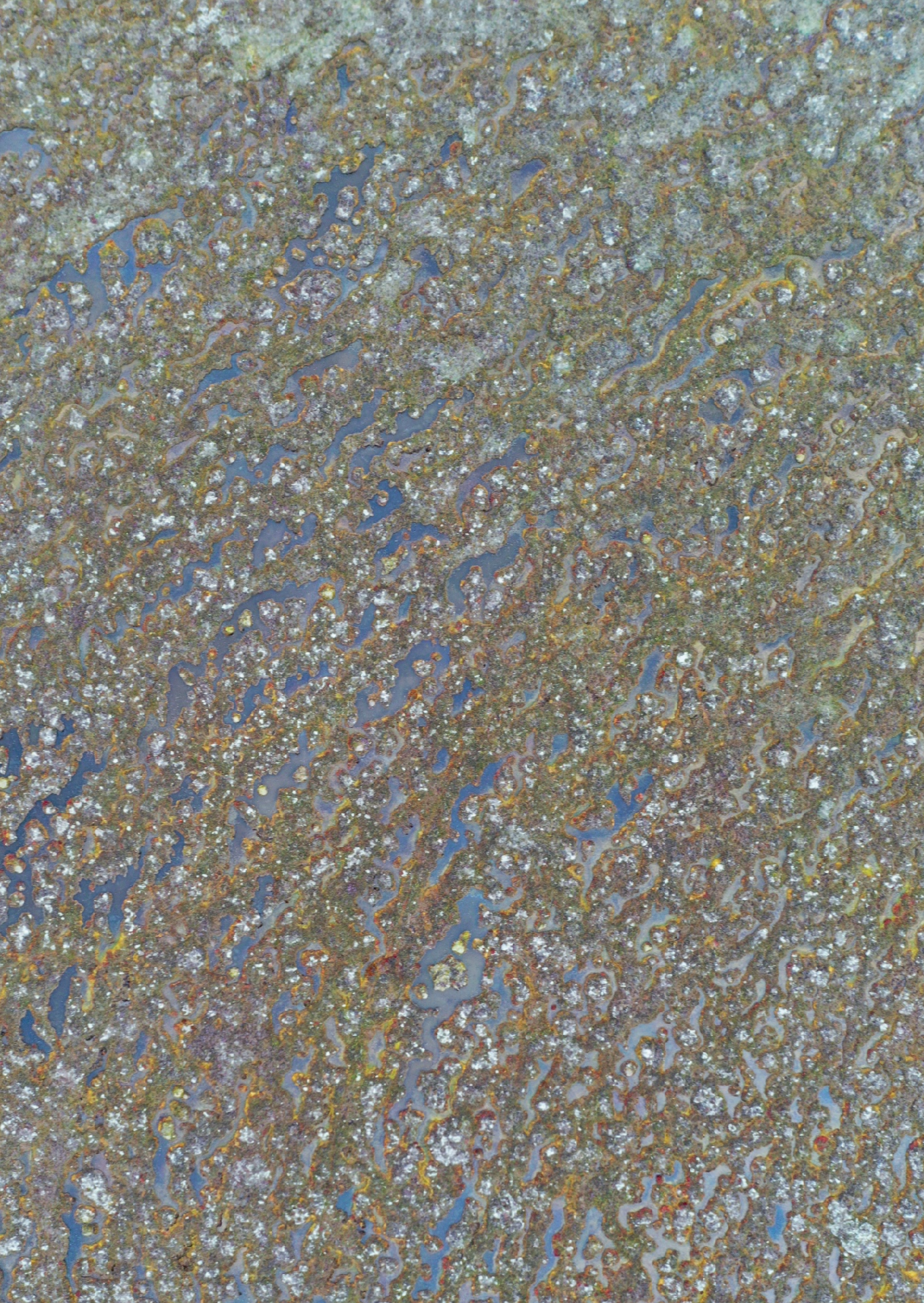
2.6 Implications of shifting microform distributions for peatland functioning

Because microforms play a key role in the carbon balance of peatlands through the differential rates of carbon accumulation and decomposition between microforms (Loisel & Yu, 2013b; Lunt et al., 2019; Riutta et al., 2007; Strack, Waddington, et al., 2006; Waddington & Roulet, 1996), shifts in microform distributions due to surface drying and warming will invariably lead to changes in the carbon balance of a peatland, although the exact direction and magnitude of these changes are still unclear. While microforms have shown remarkable resistance to changes in environmental conditions like climate change through their ability to perpetuate wet conditions with negative feedback mechanisms (Baird et al., 2016; Belyea & Clymo, 2001; Nungesser, 2003), they have also shown to respond rapidly even to small external forces once certain environmental thresholds are passed that favour one microform over the other (Belyea & Malmer, 2004; Dieleman et al., 2015; Wilson & Agnew, 1992). Initially, loss of hollows in favour of lawns and hummocks as observed in our study may lead to an increase in the carbon sink function of peatlands through reduced methane emissions (Bubier et al., 1993; Strack, Waller, et al., 2006; Strack & Waddington, 2007) and increased plant productivity of lawns and hummocks as opposed to hollows (Lunt et al., 2019; Munir et al., 2014; Straková et al., 2012; Waddington et al., 1998). Moreover, in the early stages of surface drying, drought-adapted *Sphagnum* species could expand laterally at the cost of wet-adapted *Sphagnum* species (Breeuwer et al., 2009; Robroek, Limpens, Breeuwer, & Schouten, 2007; Robroek, Limpens, Breeuwer, Crushell, et al., 2007), which would lead to lower decomposition rates, and thus higher net carbon sequestration (Johnson & Damman, 1991; Turetsky et al., 2008). At longer timescales, however, *Sphagnum* productivity declines rapidly under both drying and warming climate conditions, while vascular plant productivity increases instead (Bragazza et al., 2016; Dieleman et al., 2015; He et al., 2016; Jassey et al., 2013; Norby et al., 2019; Rastogi et al., 2019). Release of soil carbon through decomposition would then increase not only due to enhanced soil oxygenation, but also because vascular plant litter is more labile than *Sphagnum* litter (Dorrepaal et al., 2005; Lang et al., 2009; Walker et al., 2016), and promotes microbial activity (Bragazza et al., 2013, 2015; Gavazov et al., 2018; Robroek et al., 2016), especially under elevated temperatures (Mao et al., 2018; Zeh et al., 2019, 2020). This may lead to a positive feedback that enables even further shrub expansion (Bragazza et al., 2013; Heijmans et al., 2013; Holmgren et al., 2015).

Taken together, prolonged surface drying would eventually result in a reduction in carbon sequestration. Furthermore, surface drying and an increase in vascular plant cover over *Sphagnum* also lead to higher risk of peat fires (Nelson et al., 2021; Turetsky et al., 2015), as well as higher intensity peat fires (Benscoter et al., 2015; Benscoter & Wieder, 2003; Blier-Langdeau et al., 2021; Shetler et al., 2008; Turetsky et al., 2011) which can cause carbon emissions that far exceed rates of carbon uptake, even under enhanced vascular plant productivity (Turetsky et al., 2011). Although assessment of net changes in the carbon balance of peatlands with shifting microform distributions would require a systematic survey of the carbon fluxes associated with different microforms, there is increasing consensus that preservation of wet conditions minimizes carbon efflux from peatlands despite increased methane emissions (Evans et al., 2021; Günther et al., 2020; Huang et al., 2021), especially under projected changes in temperature and precipitation for Ireland in the upcoming decades, and the role of climate change in vegetation dynamics and fire risk. Consequently, restoration and rehabilitation of peatlands for reinstating wet surface conditions are currently carried out through several projects, including ‘The Living Bog Project’ (LIFE14 NAT/IE/000032) for twelve raised bogs SAC’s, the ‘Enhanced Peatland Decommissioning Rehabilitation and Restoration Scheme’ (EDRRS) by Bord na Móna for 80 raised bogs, and the ‘Wild Atlantic Nature’ project (LIFE18 IPE/IE/000002) for 35 blanket bog SAC sites. Such activities should remain an urgent focus in combination with preservation of remaining pristine peatlands to maintain the carbon sink function of Irish peatlands.

2.7 Conclusion

Our results show net drying of peatland microforms in protected ombrotrophic peatlands between 1978–2021. Progressive loss of wet microforms from the peat surface will likely lead to reductions in carbon sequestration and the ecosystem capacity to buffer climate extremes as peat-building *Sphagnum* mosses are replaced by dense shrubs. Consequently, preservation of remaining pristine peatlands and prompt rewetting of degrading peatlands should remain an urgent focus where possible to preserve the important carbon sink function of these ecosystems. Because landscape-scale microform proportions are such a strong ecological indicator for the hydrological conditions and resilience of a peatland ecosystem, monitoring of vegetation and microform dynamics using drones can provide an invaluable role in assessing the progress of restoration and rewetting efforts.



Chapter 3

Less is more: optimizing vegetation mapping in peatlands using unmanned aerial vehicles (UAVs)

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Abstract

1. Northern peatlands are inaccessible wetlands that serve important ecosystem services to humans, including climate regulation by storing and sequestering carbon. Unmanned aerial vehicles or drones are ideal to map vegetation and associated functions in these ecosystems, but standardized methods to optimize efficiency (highest accuracy with lowest processing time) are lacking.

2. We collected high-resolution drone imagery at three different altitudes (20m, 60m, and 120m) of two Irish peatlands contrasting in pattern complexity and evaluated to what extent classification accuracy of vegetation patterns (microforms and plant functional types) changed using different flight altitudes, minimum segment size and training/testing sample size. We also analysed the processing time of all classifications to find the most efficient combination of parameters.

3. Classification accuracy was consistently high (>90%) and estimated areas of both patterns were uniform among all flight altitudes, independent of pattern complexity. Minimum segment size and training/testing sample size were also important parameters affecting the efficiency of classifications. Total processing time from imagery capture to final map was 19–22 times faster with drone imagery at 120m altitude than at 20m, and seven times faster than at 60m.

4. Our findings suggest that flying at the maximum legal altitude of 120m is the most efficient approach for landscape-scale mapping of vegetation in peatlands or other ecosystems with similar short vegetation structure. We conclude that flying higher is always more efficient as long as the pixel size of drone imagery remains under the pixel size of the pattern under investigation.

Keywords: peatlands, vegetation patterns, unmanned aerial vehicles (UAVs), heterogeneous landscapes, remote sensing, machine learning

3.1 Introduction

Northern peatlands (hereafter: peatlands) provide key ecosystem services to humans, like drinking water provision, flood control, water purification, biodiversity, and climate regulation through their natural ability to store disproportionally large amounts of carbon. Peatlands represent only about 2% of the earths' surface (Xu et al., 2018), yet store between 472–620Gt of soil carbon (Yu et al., 2010), compromising more than one-third of all terrestrially stored soil carbon (Rydin & Jeglum, 2013), and more than 90% of the global peatland carbon pool (Yu, 2011). Many peatland functions, including carbon sequestration, are strongly linked to vegetation structure (species composition, biomass, and spatial organisation), potentially enabling upscaling of this climate regulating service through vegetation patterns.

Peatland vegetation commonly exhibits characteristic spatial patterns in the landscape resulting from microtopographic irregularities called microforms, ranging from elevated moist hummocks, wet-moist lawns, wet depressions (hollows), to open water (Figure 3.1). Because the plant species and plant functional types (PFTs) occurring along this microtopographical gradient differ in functional traits, the distribution of microforms and their associated vegetation are commonly used indicators for peatland functioning, such as its hydrological condition and biogeochemical fluxes (Couwenberg et al., 2011b; Lees et al., 2018; Schaepman-Strub et al., 2009). Yet, upscaling this information from plot-level to larger areas is complicated by the scale and heterogeneity of these patterns (Räsänen & Virtanen, 2019; Siewert & Olofsson, 2020), which range from 0.01–1m for PFTs to 1–10m for microforms, falling below the current spatial resolution of commercial satellites.

In recent years, remote sensing with unmanned aerial vehicles (UAVs) or drones has specifically gained much attention for its potential role in mapping and monitoring peatland vegetation and its functions. Drones can already capture the fine-scale heterogeneity of peatland microtopography and associated vegetation with unprecedented level of detail and will only evolve further and more rapidly in the upcoming years (Anderson & Gaston, 2013; Manfreda et al., 2018), making them an ideal bridge between field-based measurements and satellite remote sensing in these ecosystems. Besides, the distinct spectral differences between vegetation types along the microtopographical gradient in combination with their relatively flat topography makes peatlands inherently suitable for mapping fine-scale vegetation patterns as it also notably improves the accuracy of drone-derived photogrammetry products (Czapiewski, 2022; Lovitt et al., 2017). Multiple studies have highlighted the great potential of drone imagery for mapping fine-scale peatland vegetation patterns (e.g. Beyer et al., 2019; Bhatnagar et al., 2021; Lehmann et al., 2016; Palace et al., 2018; Räsänen, Aurela, et al., 2020; Räsänen et al., 2019; Riihimäki et al., 2019; Steenvoorden et al., 2022). However, while promising, the relatively long processing times and limited spatial coverage of drones together with the unknown sensitivity of flight and image processing parameters to the complexity of spatial patterns currently hamper upscaling of the approach.

In this study, we sought to improve the efficiency of drone-based vegetation mapping (i.e. reducing total processing time without compromising on accuracy) by investigating the role of several flight and image processing parameters (flight altitude, training/testing sample size, and minimum segment size) on total processing time and accuracy of mapping peatland vegetation patterns. More specifically, we classified microforms and plant functional types in two peatlands with contrasting pattern complexity (heterogeneous vs homogeneous vegetation) using drone-derived remote sensing products taken at three different flight altitudes. We hypothesize that: 1) classification accuracy of vegetation patterns increases with larger sample sizes and segment sizes reflecting the real patchiness of vegetation patterns, 2) classification accuracy of vegetation patterns is independent of flight altitude, 3) classification accuracy increases in peatlands with more heterogeneous vegetation patterns, and 4) classification efficiency is significantly higher using imagery at 120m altitude than imagery at lower altitudes.

3.2 Materials and methods

3.2.1 Study area

We selected two Irish ombrotrophic peatlands based on their contrasting levels of pattern complexity: well-developed heterogeneous patterns in Carrowbehy and less developed and more homogeneous patterns in Raheenmore (Figure 3.1). Carrowbehy is a western raised bog complex of 343ha that exhibits a very clear hummock-lawn-hollow pattern with occasional open water pools in the central and hydrologically most intact areas of the peatland (called the central ecotope; Figure 3.1). While Carrowbehy has experienced moderate domestic peat cutting in its recent history, peat cutting has ceased here since 2003 (Fernandez et al., 2014), and it is currently a prime example of remaining ecohydrologically intact raised bogs in Ireland. Raheenmore is an eastern raised bog of 210ha situated in the Irish Midlands and is one of the last surviving raised bogs in the eastern part of the country. In contrast with Carrowbehy, the central ecotope of Raheenmore has a less developed microtopography, lacking permanent pools and extensive hollows. Rather, the vegetation patterns of Raheenmore are more homogeneous and are largely dominated by hummocks interspersed with lawns filled with graminoids and some peat mosses (Figure 3.1). Both peatlands are part of Irelands' Special Areas of Conservation (SAC's) network under the EU Habitats Directive (92/43/EE; Mackin et al., 2017; National Parks and Wildlife Service, 2018).

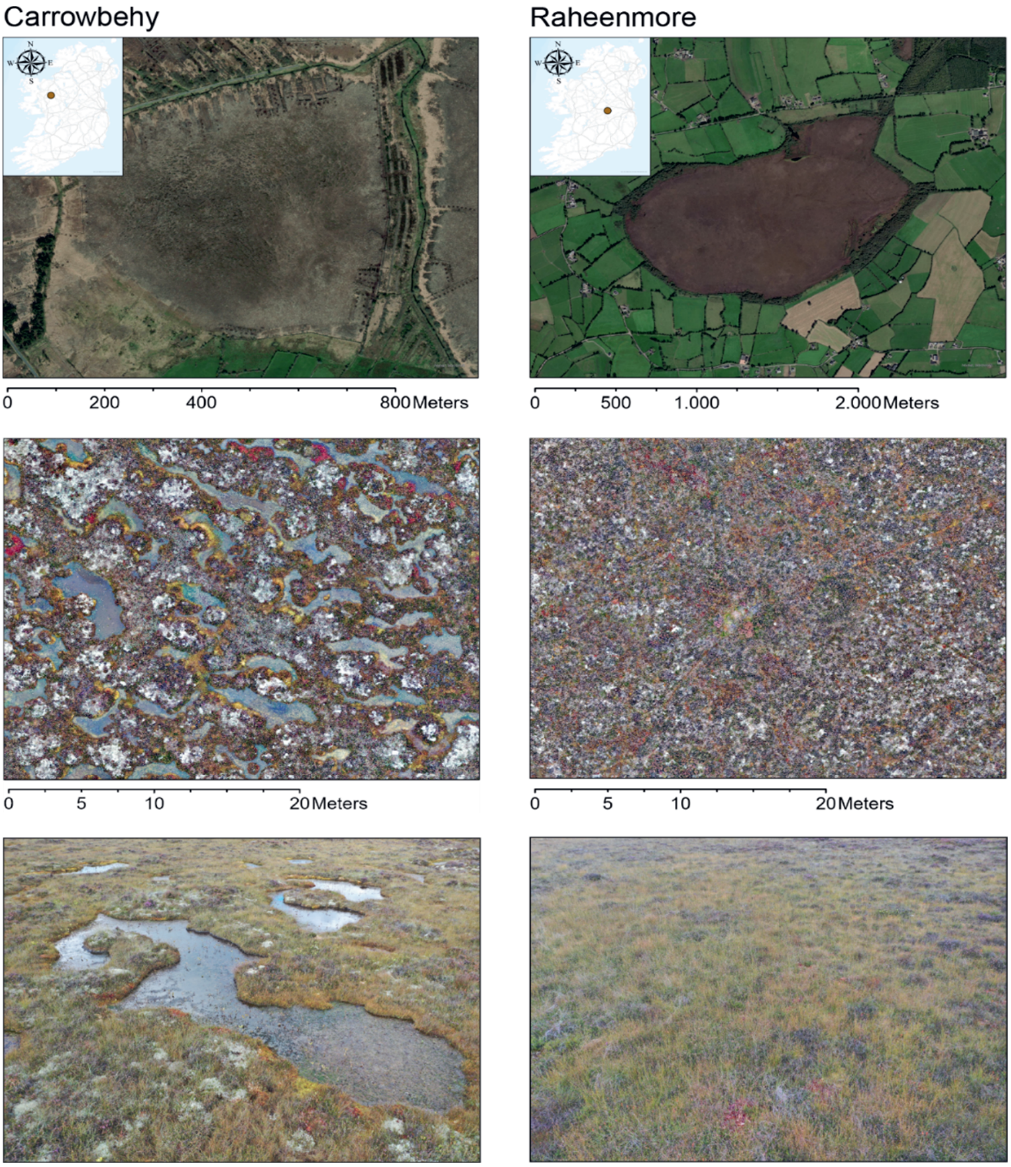

Figure 3.1 Study area maps showing the characteristic vegetation patterns in the central areas of Carrowbehy (left) and Raheenmore (right). The top images show both studied peatlands as well as their location in Ireland (inset). Presented in the middle pictures are the vegetation patterns of Carrowbehy and Raheenmore as seen from drone imagery at 20m altitude using a DJI Mavic 2 Pro. The bottom images show the vegetation patterns of both peatlands from images taken at 3m altitude.

3.2.2 Drone imagery capture

We collected drone images of Carrowbehy and Raheenmore on 14 and 21 September 2021 respectively using a DJI Mavic 2 Pro drone with Hasselblad L1D-20c red-green-blue (RGB) colour sensor camera. We used no intrinsic camera parameters, except for the default camera calibration present in the EXIF information, which is limited to focal length (10.3mm). All camera parameters were determined or optimized during the photogrammetric processing. We used DJI Ground Station Pro to design automated flights of 1ha (or more depending on altitude) at an altitude of 20m, 60m, and 120m above ground level for each peatland and a forward/side image overlap of 80/80%, extending flight lines well beyond our region of interest to increase the number of overlapping images at the edges of our plot for use during photogrammetry. We decided upon using these altitudes because 120m is the maximum legal flight altitude using consumer grade drones, 60m is half of the maximum legal flight altitude and half the resolution of imagery at 120m, and 20m is an extremely low flight altitude reaching sub-centimetre spatial resolution. To allow for georeferencing of the stitched drone images at each flight altitude, we distributed four 30x40cm checkerboard ground control points around the edges of each 1ha plot and measured their position using a Topcon HiPer HR real-time kinematic (RTK) and TopNET+ global navigation satellite system (GNSS) with 1–3cm accuracy. All flights were conducted within one hour of solar noon under fully cloudy conditions to minimize the effect of shade, where wind speeds varied between low to moderate wind speeds up to 19km/h.

3.2.3 Pre-processing drone imagery

After all drone flights were conducted, we pre-processed all drone-derived imagery products before classifying vegetation patterns within each orthomosaic. First, we used ortho-mapping software in ArcGIS Pro 2.8.2 to colour balance the drone images and produce a stitched RGB orthomosaic of each flight, as well as to create a high-resolution Digital Terrain Model (DTM) with 5x pixel size of each orthomosaic (default setting) using the photogrammetric data contained within each individual drone image (Table S3.1). More specifically, we created the DTM using extended terrain matching, which is a feature-based stereo matching technique for generating high density point clouds. Hereafter, we georeferenced each orthomosaic using the ground control points and clipped the georeferenced orthomosaics to a rectangular polygon of 1ha and 0.56ha for Carrowbehy and Raheenmore respectively, because the orthomosaic of Raheenmore at 20m altitude was only 75x75m.

Second, we grouped all pixels within each orthomosaic into segments (objects) using a mean-shift clustering algorithm based on similarity in spectral and spatial characteristics of the raster image. To calibrate the optimal minimum segment size for classification of microforms and plant functional types (PFTs) in our study, we carried out this segmentation fourteen times for both patterns in both peatlands (total of 60 segmentations) using the imagery at 120m altitude (Table 3.1). We started with a minimum segment size of 0.01m^2 ground area (0.1x0.1m) and increased minimum segment size by 0.05x0.05m after every iteration of the classification algorithm up to a minimum segment size of 0.5625m^2 (0.75x0.75m). We only performed this analysis at 120m because the ground area is independent of flight altitude, and we argue that repeated segmentations at lower altitudes would therefore likely lead to very similar results.

Third, we detrended each DTM by fitting a second-order polynomial function through the elevation points in the DTM, and subsequently subtracted the DTM from the fitted trend function. This detrended DTM represents relative microtopographical differences within the orthomosaic more realistically and was needed because the DTM of each orthomosaic was slightly sloping downwards from the centre to the margin of the peatlands.

Lastly, we calculated several RGB-derived vegetation colour indices as additional predictor variables in the classification of both microforms and PFTs to further emphasise spectral differences between vegetation classes. Ultimately, we employed a total of 25 predictor variables in the classification of both microforms and PFTs, consisting of the mean and standard deviation of RGB values, mean of the Hue-Saturation-Value colour model, ten vegetation colour indices combining two or more RGB bands, elevation (minimum, maximum, and mean) and three shape metrics (pixel count, rectangularity, and compactness), computed separately for all segments in each orthomosaic (Table S3.2).

3.2.4 Ground truth data

We divided vegetation patterns in our study into microforms and PFTs because they are two common conceptualizations used in mapping vegetation patterns and functions in peatlands. Hereafter, we further subdivided each vegetation pattern into classes based on drone-visible indicator species (or the lack thereof) and their associated position along the microtopographical gradient as seen from the newly developed orthomosaics. Microforms were subdivided into three classes: 1) hollow, 2) lawn, and 3) hummock (Table S3.3), while PFTs were subdivided into five classes: 1) peat moss, 2) shrub, 3) graminoid, 4) lichen, and 5) water/bare peat (Table S3.3).

For classification of microforms, we initially created 500 randomly placed points within each orthomosaic for Carrowbehy and used the highest resolution orthomosaic at 20m altitude as a reference dataset to create training/testing samples for use in classification. The geographical locations of these point measurements were then linked to the values of the predictor variables within the computed segment by which they were contained to develop the full training/testing dataset. We increased total training/testing sample size for microforms to 625 points (375 hummock, 150 lawn, and 100 hollow) by randomly adding new points until we reached a rounded-out approximation of area-proportional allocation of training/testing samples for Carrowbehy. For classification of PFTs, we instead adopted a targeted sampling approach, where we placed 100 points per PFT per orthomosaic for Carrowbehy (500 total; five PFTs) to prevent underrepresentation of uncommon PFTs in each orthomosaic. To evaluate the effect of training/testing sample size on classification accuracy, we performed a sensitivity analysis on the training/testing samples during classification of microforms for Carrowbehy at 120m altitude where we systematically reduced the proportion of total training/testing samples from 100% to 10% with steps of 10%. The results of this sensitivity analysis were then used to adjust the total training/testing sample size for classification of microforms for Raheenmore to a reduced sample size that still had consistent accuracy compared to the full sample size (see also 3.3.1.2; Table 3.1). For PFTs we used the same sensitivity analysis as for microforms, after which we also adjusted the total training/testing sample used for classification of PFTs for Raheenmore to the reduced sample size where classification accuracy remained consistent (see also 3.3.1).

3.2.5 Vegetation pattern classification

We classified vegetation classes of each pattern based on selected segments using the training/testing samples within each orthomosaic in combination with the ensemble classifier Random Forest (Breiman, 2001) using Python's Scikit-learn module (Pedregosa et al., 2011) with the 25 predictor variables as input. We used Random Forest as it is a robust and interpretable machine learning algorithm with little demand on computational power (Belgiu & Drăguţ, 2016). To fit the Random Forest models, we first removed redundant predictor variables from the whole training/testing sample of each orthomosaic using the Boruta feature-selection algorithm (Kursa & Rudnicki, 2010). We then split the training/testing samples for each orthomosaic using stratified K-fold cross-validation (CV) with a ratio of 80:20 for training versus testing (analogous to 5-folds) because it minimized variance of CV model accuracy in our study as compared to repeated K-Fold cross-validation or a larger number of folds (G. Jiang & Wang, 2017). We kept hyperparameters of the Random Forest classifier at default values as accuracy improvements through hyperparameter tuning were negligible (<1%). Classification accuracy per vegetation class as well as final classification accuracy of each orthomosaic were computed by averaging precision, recall, and F1-score over all folds in the Random Forest model using the testing samples. An average value of 1 then indicates a perfect prediction, while any value in between 0–1 (or 0–100%) indicates the probability that a testing sample is correctly classified. We classified all segments within each orthomosaic by taking the most frequently classified vegetation class for each segment over all folds. Lastly, we retrieved an overall ranking of variable importance for each classified image by computing the Gini importance, which we used as it is a commonly used measure for variable importance in peatland studies (Behnamian et al., 2017; Millard & Richardson, 2015). Because variable importance rankings for each plot varied between Random Forest model runs (i.e. folds), we averaged Gini importance over all folds to receive more stable mean importance values for each classification (Behnamian et al., 2017). In cases where a predictor variable was removed through Boruta, variable importance was set to 0.

3.2.6 Stratified estimation of mapped class areas

After each orthomosaic was classified, we used the confusion matrix and mapped class area (m^2) from the classification of each orthomosaic to estimate accuracy and quantify uncertainty of the mapped class areas using stratified estimation (Olofsson et al., 2013, 2014). More specifically, we used the ratio between true positives, false positives, true negatives, and false negatives for each class within the confusion matrix in combination with the mapped area of each class to compute their error-adjusted area estimates and confidence intervals as well as recalculating the accuracy measures and confidence intervals hereof using the stratified area estimates. Stratified estimation represents the uncertainty in mapped areas due to misclassifications more realistically, whereas solely using sample counts from the confusion matrix as means of assessing classification accuracy can severely underestimate or overestimate the true accuracy and area of vegetation classes. This is crucial, especially since variability in mapped class area estimates resulting from misclassifications could have cascading effects when for instance developing models that link vegetation patterns to functions such as carbon fluxes (Olofsson et al., 2013). Stratified estimation is a transparent and statistically robust approach to assess accuracy and estimate mapped areas of vegetation classes, and therefore allows for more effective use of drone imagery products in later analyses. Besides, by taking this uncertainty into account, it allowed for better comparison of the consistency between mapped areas of each vegetation class at the different altitudes used in this study. A workflow of our full research methodology can be seen in Figure S3.1.

Table 3.1 Overview of the imagery that was used to evaluate each hypothesis of the study. First, we used the imagery of both Carrowbehy (heterogeneous) and Raheenmore (homogeneous) at 120m altitude to calibrate the optimal minimum segment size for the study. We then used the results of the sensitivity analysis of training/testing sample size for Carrowbehy at 120m altitude to adjust the training/testing sample size for Raheenmore. Afterwards, we applied these calibrated image processing parameters to all subsequent classifications for both peatlands. A check mark (green) is used to indicate that a dataset was used during analysis for evaluating a specific hypothesis, whereas a cross (red) indicates that a dataset was not used in analysis for evaluating a specific hypothesis.

Hypotheses	**Carrowbehy (heterogeneous)**			**Raheenmore (homogeneous)**		
	20m	**60m**	**120m**	**20m**	**60m**	**120m**
Hypothesis 1 (Sensitivity analyses)	✗	✗	✓	✗	✗	✓
				Adjust total training/testing sample size of Raheenmore		
	Apply calibrated optimal minimum segment size to all subsequent classifications					
Hypothesis 2 (Flight altitude)	✓	✓	✓	✓	✓	✓
Hypothesis 3 (Pattern complexity)	✓	✓	✓	✓	✓	✓
Hypothesis 4 (Classification efficiency)	✓	✓	✓	✓	✓	✓

3.3 Results

3.3.1 Sensitivity analyses

3.3.1.1 Optimal minimum segment size

Before classifying microforms and plant functional types (PFTs) at all three flight altitudes, we first classified both vegetation patterns at 120m altitude at both peatlands using a total of fourteen different minimum segment sizes ranging from 0.1m to 0.75m to determine the optimal minimum segment size for classification of each vegetation pattern. This analysis showed that classification accuracy is highly dependent on the minimum size of the segments within an orthomosaic, and that minimum segment size also strongly influences classification time. Overall, classification accuracy and variance were comparable for both peatlands and for both vegetation patterns until a minimum segment size of 0.25m (Figure 3.2; Table S3.4–S3.7), after which accuracy started dropping and variance started increasing notably up until a minimum segment size of 0.75m. In addition, reductions in processing time were largest from 0.1–0.25m, whereas reductions in processing time from 0.25–0.75m were only twelve seconds on average for all four classifications (Table S3.4–Table S3.7; Figure 3.2). These results highlighted that a minimum segment size of 0.25m is most efficient independent of the studied vegetation pattern (microform or PFT) or pattern complexity, and we therefore decided to use a minimum segment size of 0.25m for all further analyses.

3.3.1.2 Training/testing sample size

After determining an optimal minimum segment size of 0.25m, we performed our sensitivity analysis on the training/testing sample size for Carrowbehy. For microforms, the sensitivity analysis highlighted that classification accuracy and variance of CV model accuracy were consistent until 40% of the total training/testing sample size remained (Table S3.8; Figure 3.3). The sensitivity analysis for PFTs in Carrowbehy showed that classification accuracy and variance of CV model accuracy were consistent until 50% of the total training/testing sample size remained (Table S3.9; Figure 3.3). These results underscored that total training/testing sample sizes of 625 and 500 for microforms and PFTs respectively were more than adequate to reach consistent classification accuracies for Carrowbehy. Consequently, we used reduced total training/testing sample sizes as ground truthing data during classification of microforms and PFTs for Raheenmore. Here, we created only 250 random points (40% of 625 points) of microforms within each orthomosaic and rounded out these points to a total training/testing sample size of 275 points (200 hummock and 75 lawn points). For PFTs, we placed only 50 points per PFT (200 in total; four PFTs) per orthomosaic in Raheenmore as training/testing samples for use in classification.

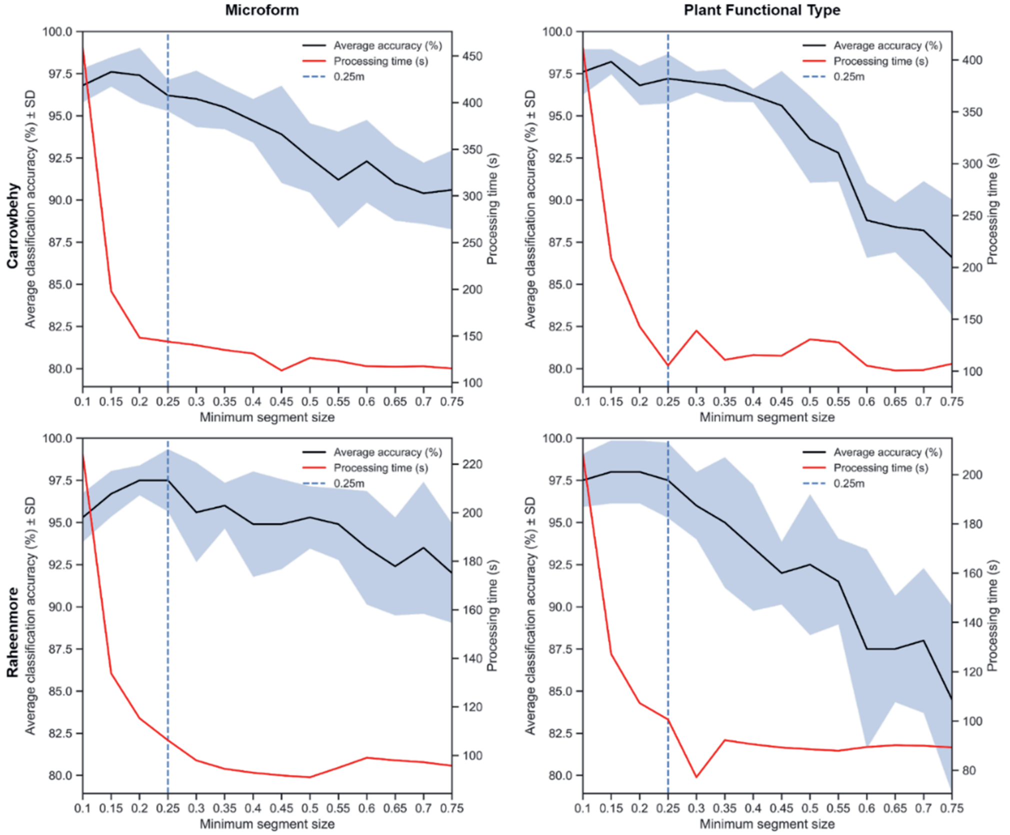

Figure 3.2 Relationship between average classification accuracy and processing time of microforms (left) and plant functional types (right) for heterogeneous Carrowbehy (top) and homogenous Raheenmore (bottom). The black line represents the average classification accuracy over five folds using stratified K-fold cross-validation (black), with the blue shaded area indicating the standard deviation.

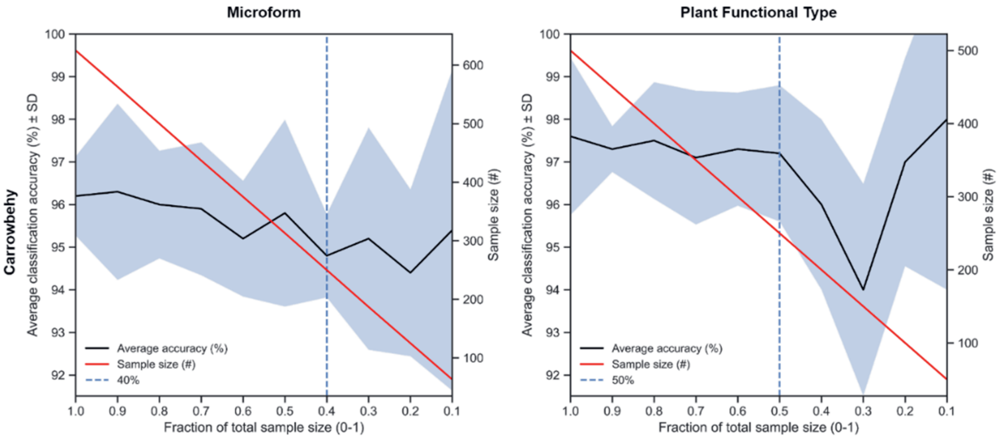

Figure 3.3 Relationship between total sample size (and fraction of total sample size) on the accuracy of classifications of microforms (left) and plant functional types (right) for Carrowbehy using a minimum segment size of 0.25m. The black line represents average classification accuracy over five folds using stratified K-fold cross-validation, with the blue shaded area indicating the standard deviation. The red line indicates total sample size, and the vertical dotted line highlights the minimum fraction for consistent classification results (40% for microforms and 50% for plant functional types).

3.3.2 Vegetation pattern classifications

3.3.2.1 Microform classifications

Classified images of microforms showed average accuracies of well over 90% at all flight altitudes, where the lowest accuracy was 95.2% (Carrowbehy at 60m) and the highest accuracy was 97.8% (Raheenmore at 20m). Besides, classification reports for each classified orthomosaic highlighted that accuracies per microform were also generally very high, with accuracies reaching at least 90% in all cases (Table S3.10). Misclassifications in Carrowbehy most often occurred between lawn and hummocks, but occasionally also between hummock and hollow (Table S3.15), likely explained by occasional similarities in spectral reflectance between species of different microforms (see also discussion 4.1). In Raheenmore, only hummock and lawn were present, which were therefore always misclassified as each other. Analysis of variable importance emphasized that both vegetation colour indices and elevation predictor variable categories were always important in classification of microforms for both peatlands, whereas RGB values and shape metrics were hardly ever important or even included the Random Forest models after feature selection with Boruta (Figure S3.3). The high classification accuracies of all microforms in both peatlands show that the detectability and mappability of microforms in our study was extremely good independent of pattern complexity.

Mapped class areas for each classification emphasized that hummock was by far the largest class at all three altitudes for both peatlands (Figure 3.4; Figure 3.5), followed by lawn and hollow, which both occurred approximately in equal amounts in all peatlands (Figure 3.4). After stratified estimation, error-adjusted areas for each microform changed slightly in each peatland (Figure 3.4; Table S3.12), but the substantially overlapping confidence intervals for estimated areas of all microforms underline that these values are not significantly influenced by flight altitude. These findings signify that carrying out drone flights below 120m altitude (2.7cm pixel size in our study) provided no benefit to classification accuracy of microforms.

3.3.2.2 Plant functional type classifications

Like microforms, classified images of plant functional types (PFTs) also showed average accuracies of well over 90% at all flight altitudes. Here, lowest classification accuracy was 92.5% (Raheenmore at 20m) and the highest accuracy was 97.5% (Raheenmore at 120m). Classification reports for each classified orthomosaic showed that accuracies per PFT were also generally very high (Table S3.11), with accuracies reaching at least 90% for all classes but graminoid at 20m for both Carrowbehy (87.4%) and Raheenmore (84.6%), highlighting that graminoid was most difficult to classify at low flight altitudes. Misclassifications of PFTs in both Carrowbehy and Raheenmore most often occurred between graminoid and shrub and between graminoid and lichen (Table S3.15), likely also explained by occasional similarities in spectral reflectance between classes (see also discussion 3.4.1). Variable importance for classifications of PFTs differed strongly when compared to those of classifications of microforms in both peatlands. Here, mean RGB values, Hue-Saturation-Value colour model values and vegetation colour indices were the most important predictor variable categories, whereas elevation was hardly ever of importance in the Random Forest models (Figure S3.3). This is likely caused because the same PFTs can occur at multiple locations along the microtopographical gradient as well as in multiple microforms. Based on the consistently high classification results of PFTs for both peatlands, we argue that pattern complexity has no effect on the detectability of PFTs in our study.

Mapped class areas for each classification highlighted that shrub and graminoid were the most dominant PFTs in each peatland, followed by peat moss, lichen, and water/bare peat (occurred in Carrowbehy only; Table S3.13; Figure 3.4; Figure 3.5). After stratified estimation, error-adjusted areas for each PFT changed slightly in each peatland. The confidence intervals show that ranges in error-adjusted areas for shrub and graminoid are highest in both locations at 20m because of their reduced classification accuracy, and that ranges in error-adjusted areas are also large for lichen in Raheenmore because lichen was sometimes classified as graminoid, which occurred in large proportions. Nevertheless, the confidence intervals for estimated areas of PFT classes for all altitudes still overlap substantially, highlighting that these estimated areas are also consistent at all three altitudes for both peatlands (Table S3.13; Figure 3.4). These results also signify that drone flights below 120m altitude provide no benefit to classification accuracy of PFTs, and that classification accuracy even improves at higher altitudes instead because of reduced misclassifications between shrub and graminoid.

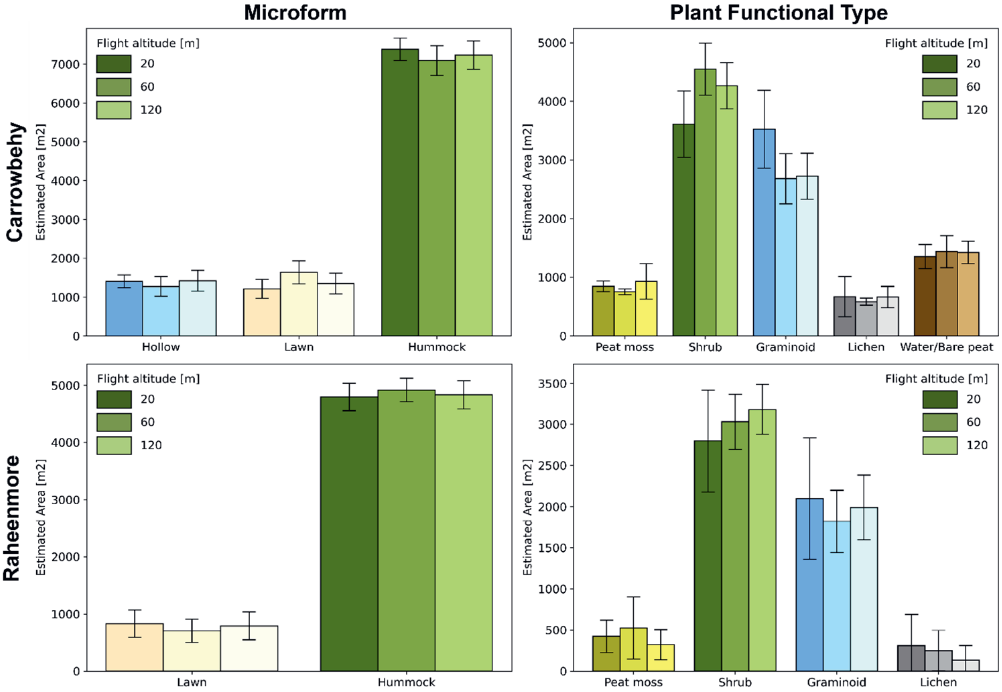

Figure 3.4: Overview of estimated areas (m^2) with confidence intervals for classification of microforms (left) and plant functional types (right) at all three altitudes (20m, 60m and 120m) for both studied peatlands with varying pattern complexity: Carrowbehy (top, heterogeneous) and Raheenmore (bottom, homogeneous). Bars for each vegetation class of each pattern represent estimated areas at 20m (left), 60m (center) and 120m (right).

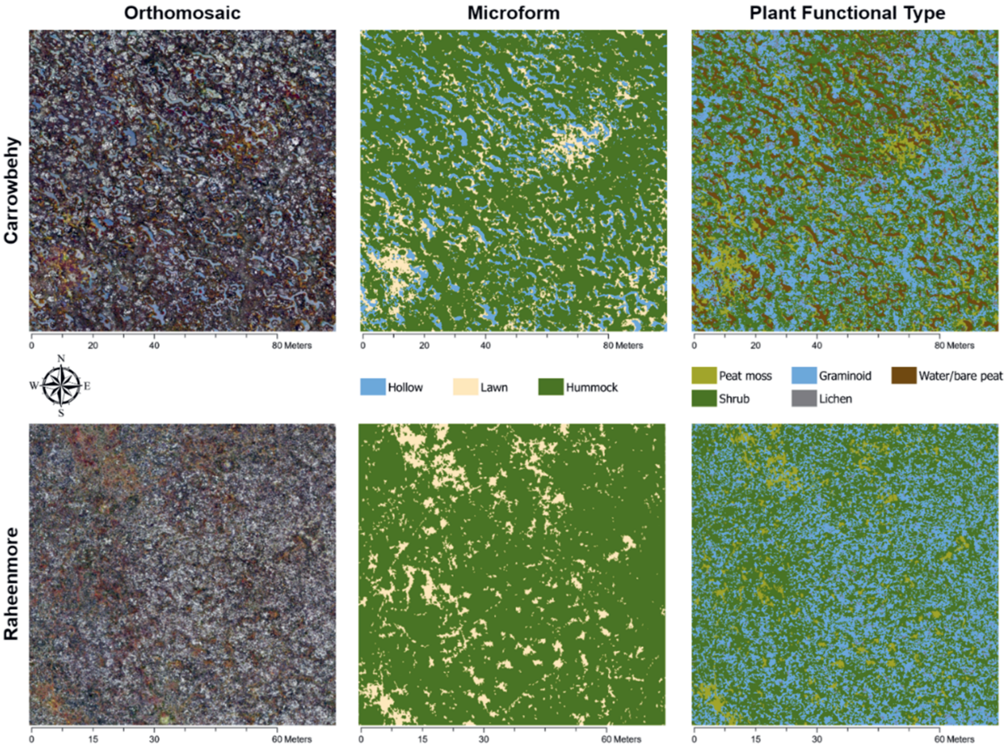

Figure 3.5 Maps showing the classification results at 120m altitude for both studied peatlands with varying pattern complexity: Carrowbehy (top, heterogeneous) and Raheenmore (bottom, homogeneous). Represented for each peatland are the orthomosaic at 120m altitude (left), classified map of microforms at 120m altitude (centre) and classified map of plant functional types at 120m altitude (right).

3.3.2.3 Classification efficiency

To analyse the efficiency of mapping microforms and plant functional types in our study using drone imagery, we summarized total image capture and processing time for the imagery at each altitude using 80/80% forward/side overlap and a minimum segment size of 0.25m (Figure 3.6; Table S3.14). Here, we assumed that classification accuracy of both vegetation patterns was consistent at all three altitudes for both peatlands based on the largely overlapping confidence intervals of estimated areas for each class within a vegetation pattern. Total processing time from imagery capture to final map was approximately seven times faster at 120m altitude than at 60m and between 19–22 times faster than at 20m for both vegetation patterns in both peatlands (Figure 3.6). A considerable amount of this processing time at lower altitudes was spent capturing and pre-processing the drone imagery (Figure 3.6; Table S3.14), which is most likely caused by the large number of pixels per area in 20m imagery as opposed to imagery at 60m and 120m (Table S3.1). We therefore argue that aside from other flight and processing parameters, flying at the maximum legal flight altitude of 120m is by far the most efficient approach for mapping peatland vegetation patterns, at least in our study.

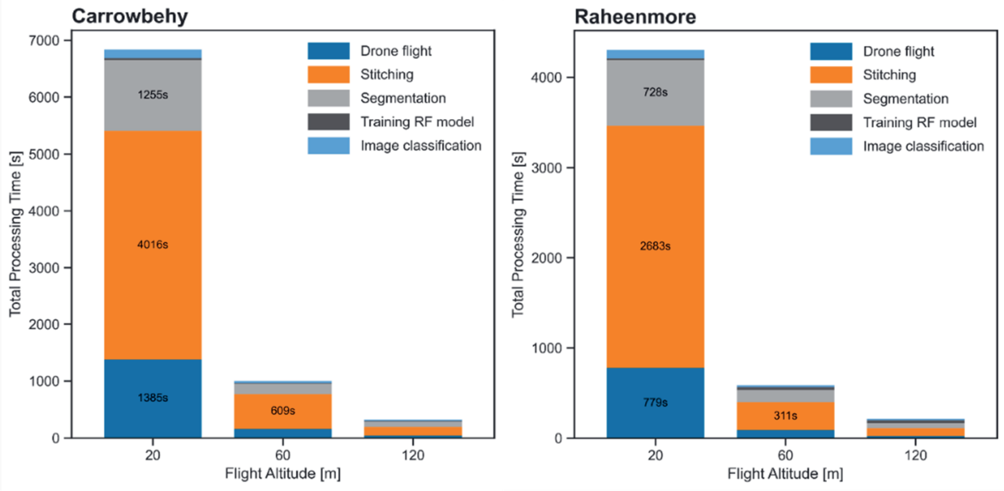

Figure 3.6 Stacked bar plots highlighting the total processing time for different processes carried out during classification of microforms and plant functional types at three altitudes (20m, 60m and 120m) in two peatlands (Carrowbehy and Raheenmore) with contrasting complexity. Because processing times of different patterns within a peatland were near equal, the presented processing times are averaged over the classifications of microforms and plant functional types for that specific peatland and altitude. Processing times are presented in chronological order from image capture to final map. Bars with processes that compromised less than 300 seconds are not labelled for visual clarity.

3.4 Discussion

3.4.1 Consistency of peatland vegetation pattern classifications

We found that classification accuracy of vegetation was not affected by flight altitude up to 120m, pattern complexity or spatial scale of the pattern (microforms vs plant functional type). We attribute the high consistency of the classification accuracy to three main factors: 1) the high spectral separability of peatland vegetation, 2) the role of topographical data on class separability, and 3) optimization of spatial resolution and segmentation scale. While drones may be particularly suited for landscape-scale vegetation mapping of open, tree-less peatlands, the insensitivity of classification results to pattern complexity suggests that our results are not limited to these ecosystems. Instead, we think drones can as efficiently be used for mapping vegetation in other ecosystems with similar short vegetation structure, such as moorlands, heathlands, or tundra, albeit by having slightly different data and resolution requirements than peatlands.

3.4.1.1 Spectral separability

The environmental gradients associated with microtopography in peatlands strongly determine their species composition. Microforms represent a distinct set of species and PFTs that are adapted to the biogeochemical and hydrological conditions of that microform, which act as filters on plant traits and associated spectral properties (Schaepman-Strub et al., 2009). As a result, the spectral reflectance of the PFTs dominating these species assemblages often differ markedly among another (see also Figure 3.1; Table S3.3). The high spectral separability of vegetation classes at the time of our study may also explain why classification accuracy was rather insensitive to training/testing sample sizes, which was against our hypothesis. As spectral separability is co-determined by plant phenology (e.g. Palace et al., 2018; Räsänen et al., 2020), our results may be linked to the end-of-season image capture.

3.4.1.2 Topographical data

In cases where different microforms contained PFTs with similar spectral signatures, including topographical data in the classification improved separability between vegetation classes. Indeed, the elevation predictor variables were always included after feature selection with Boruta, and improved classification accuracy of microforms in both peatlands (Figure S3.3). These results align with other recent studies in peatlands, who have shown that combining spectral data with topographical data can improve the accuracy of classification in vegetation studies quite substantially (e.g. Harris & Baird, 2019; Moore et al., 2019; Räsänen et al., 2020).

3.4.1.3 Spatial resolution and segmentation scale

The results of our study show that classification success depended strongly on evaluation of both the spatial resolution of input imagery and the choice of segmentation parameters, which is in line with other peatland mapping studies (e.g. Räsänen & Virtanen, 2019; Virtanen & Ek, 2014). Because the spatial resolution of our drone imagery already significantly surpassed the minimum size of our investigated vegetation patterns even at 120m altitude (2.7cm in our study), this led to a trade-off during segmentation. Here, higher segment sizes would allow for mapping of larger features but may miss smaller and clustered patches, whereas lower segment sizes can detect small and clustered features but may also lead to noise during classification by introducing heterogeneity within vegetation classes (Räsänen & Virtanen, 2019), for instance by attributing different plant parts such as stems, leaves, flowers and even canopy shadow to different segments. In our study, higher spatial resolutions and lower segment sizes were not always better in distinguishing between vegetation classes, whereas efficiency was improved notably once spatial resolutions and segment sizes reflected the real scale of the vegetation patterns under investigation. Our sensitivity analysis showed that microforms and PFTs had an optimal minimum segment size of about 0.25m, which is likely low enough to identify smaller patches but not so small that vegetation classes show notable internal heterogeneity.

3.4.2 Improving mapping of fine-scale vegetation patterns

3.4.2.1 Choosing scales of interest

While we found a minimum segment size of 0.25m to optimize classification accuracy in this study, this is by no means the gold standard for the segmentation scale of microforms and PFTs because the size and shape of patterns can vary between vegetation classes within a peatland, as well between vegetation patterns among peatlands. For instance, while hummocks are generally large and compact, lawns and hollows are often smaller and more elongated. Besides, whereas hummocks are often compromised by multiple PFTs, lawns can be inhabited homogeneously by peat mosses. Consequently, the difficulty of segmentation is that there is often no way to know which segmentation approach produces the best classification results until the classification is carried out. For this reason, we argue that one should first investigate the size and shape at which ecologically meaningful vegetation patterns exist in their study area, and then compare the effect of various relevant segmentation scales on classification efficiency to choose the most optimal segmentation scale for that site or goal. Here, one could also make use of multi-resolution segmentation where multiple segmentation scales are used for delineation of patches of different vegetation classes (Blaschke et al., 2014; Dronova, 2015), although this is more difficult to implement in a classification algorithm.

3.4.2.2 Training/testing sample size and allocation

The results of our classifications showed consistent accuracy metrics even with only 40–50% of the original training/testing sample size, illustrating that defining an ‘optimal’ training/testing sample depends on a specific research or accuracy objective. For instance, to improve classification accuracy of Random Forest models, training/testing sample sizes should be as large as possible, and randomly distributed or at least created in a manner that allows for approximate area-proportional allocation of samples (Colditz, 2015; Millard & Richardson, 2015). However, to achieve acceptable standard errors for estimated accuracy metrics and area estimates, Olofsson et al. (2014) recommend that one should shift the sampling strategy slightly away from area-proportional allocation by increasing the sample size of uncommon classes (but not until equal allocation is reached). While we did not actively test the effect of sample size allocation on estimated accuracy metrics, we did see that variance of area estimates decreased notably in our study when total training/testing sample size was increased. Consequently, if the goal is to receive an accurate classification, ‘as large as possible’ means increasing a randomly distributed sample size up until a certain point where additional samples do not further improve accuracy. If the goal is instead to reduce standard errors of accuracy and area estimates of mapped vegetation classes, one should systematically evaluate the potential outcome of a specific training/testing sample size and sample allocation on their values until a desired confidence interval is reached. In either case, the decision is based on the specific research purpose or accuracy objective.

3.4.2.3 Less is more

Our results suggest that classifications remain consistent as long as the pixel size of drone imagery remains under the pixel size of the investigated pattern. Consequently, efficiency of mapping fine-scale vegetation patterns can likely be improved further by using drones with lower resolution sensors because these reduce overall flight time per area, total image capture, and processing time using otherwise identical flight parameters. Besides, several recent drone studies have successfully mapped vegetation patterns in northern peatlands and tundra ecosystems using lower resolution imagery between 3–16cm (Beyer et al., 2019; Palace et al., 2018; Räsänen, Juutinen, et al., 2019; Räsänen & Virtanen, 2019; Siewert & Olofsson, 2020), highlighting the possibilities of further reducing spatial resolution without compromising on accuracy. Lower spatial resolution imagery could potentially also be obtained by flying at higher altitudes, but current legislation in most countries prohibits drone flying above 120m altitude.

3.4.3 Linking patterns to functions

Because peatland vegetation patterns play such a key role in the carbon balance of peatlands, a next step in drone imagery analyses will be to link vegetation patterns to carbon related functions. Several studies have already started such analyses for carbon fluxes (e.g. Kelly et al., 2021; Lees et al., 2018; Lehmann et al., 2016; Moore et al., 2019), belowground C stocks (Lopatin et al., 2019), biomass (e.g. Cunliffe et al., 2020; Fraser et al., 2016; Räsänen, Juutinen, et al., 2020), and groundwater tables (Kalacska et al., 2018; Rahman et al., 2017). However, the major challenge for mapping vegetation patterns and functions in peatlands as well as other ecosystems with similar short vegetation structure is that drones will most likely never compete with the spatial coverage of commercial satellite imagery because of both technological and legislative limitations. Besides, these ecosystems are often large, continuous, isolated, and inaccessible. Consequently, nested drone-satellite approaches – where fine-scale drone imagery products are used to train larger-scale commercial satellite imagery (Bhatnagar et al., 2021; Riihimäki et al., 2019) – will likely become a necessity to be able to accurately and realistically upscale the fine-scale heterogeneous nature of peatland vegetation and their functions to the large scale at which they occur in the landscape. We think this factor is crucial and in need for further assessment in order to develop methods that can map and quantify peatland functions at regional and global scale. This will help us to better understand the vulnerability of global peatland carbon to predicted changes in climate and land-use in the 21st century.

3.5 Conclusion

The results of our study highlight the consistency of mapping fine-scale peatland vegetation patterns across multiple legal flying altitudes and in peatlands with both high and low pattern complexity. Based on these findings, we conclude that using otherwise identical flight and image processing parameters, flying at the maximum legal flight altitude of 120m is always significantly more efficient than flying at lower altitudes as long as the pixel size of drone imagery remains under the pixel size of the pattern under investigation. When flying at 120m altitude, drones are extremely well-suited for landscape-scale mapping of fine-scale vegetation patterns because of the flexibility and ease by which they can accurately and efficiently collect and process very high-resolution spectral and topographical data into vegetation pattern maps over relatively large areas. However, given the spatial characteristics of peatlands worldwide, we urge development of nested drone-satellite approaches to allow for further upscaling of vegetation patterns and their functions to the regional and global scale.

Chapter 4

Upscaling peatland mapping with drone-derived imagery: impact of spatial resolution and vegetation characteristics

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All supplementary material belonging to this chapter can be found in the published version through the DOI and by scanning the QR-code above.

Abstract

1. Northern peatland functions are strongly associated with vegetation structure. While large-scale monitoring of functions through remotely sensed mapping of vegetation patterns is therefore promising, knowledge on the interdependency between spatial resolution of acquired imagery, spatial vegetation characteristics and resulting mapping accuracy needs to be improved.

2. We evaluated how classification accuracy of microforms and plant functional types was affected by spatial resolution of acquired imagery and several spatial characteristics of the vegetation itself (size, shape, configuration, and diversity). To this end, we collected very high-resolution drone imagery (<0.05m) from eight Irish peatlands differing in vegetation composition and pattern complexity in September 2021 and 2022. We then resampled this imagery from pixel sizes of 0.027–1m and classified both mapping units at all unique spatial resolutions. Hereafter, we computed spatial vegetation characteristics for each of the eight classified images at 0.027m spatial resolution to determine their role in defining minimum spatial resolution requirements for both microforms and plant functional types.

3. We found that overall classification accuracy of microforms and plant functional types was consistently high (>90%) for all studied peatlands until average spatial resolutions were reached of 0.5m ± 0.2m and 0.25m ± 0.1m, respectively. However, variability within mapping units was considerable, with overall minimum spatial resolution ranging between 0.25 and 0.7m for microforms and between 0.15 and 0.35m for plant functional types. Individual classes even varied from 0.05 to 1 m. Furthermore, spatial vegetation characteristics were important drivers of minimum spatial resolution for microforms, but not for plant functional types. Particularly, peatlands with larger, compacter and more clustered microform patches could be classified with coarser spatial resolution imagery (up to 0.7m), while peatlands with small, complex, diverse and more finely distributed patches required minimally 0.25m.

4. Based on these findings, we conclude that spatial vegetation characteristics strongly determine minimum required spatial resolution and thus affect upscaling of peatland vegetation mapping beyond the landscape scale by constraining the use of specific remote sensing platforms.

Keywords: peatlands, vegetation patterns, drones, spatial resolution, remote sensing, upscaling

4.1 Introduction

Northern peatlands (hereafter, peatlands) are large, isolated, and inaccessible wetland types that store and sequester carbon in peat. These ecosystems provide key ecosystem services, like drinking water provision, water purification, recreational activities, biodiversity and climate regulation (Bain et al., 2011; Bonn et al., 2016). Peatland services or functions are often associated with fine-scale (<10m) vegetation structure (composition, biomass, and spatial organization; Couwenberg et al., 2011; Dieleman et al., 2015; Robroek et al., 2017). As a result, accurate assessment of current and future peatland functions at least partially depends on the spatio-temporal dynamics of peatland vegetation, which requires methods that can capture its fine-scaled heterogeneous nature, and can be expanded to the large spatial scales at which peatlands occur in the landscape.

Peatland vegetation typically exhibits spatial patterning associated with microtopography. These microtopographical features are called microforms and range from open water pools where the peat surface is always below the water table, to wet hollows, moist lawns, and finally to hummocks, where the peat surface reaches up to ~50cm above the water table (Belyea & Baird, 2006). Along this microtopographic gradient, the availability of water and nutrients change, creating habitats for different plant species sharing adaptations to the local conditions. As a result, microforms represent a distinct set of species and/or plant functional types that can be recognized as a coherent unit. The contrasting biogeochemical conditions also act as a filter on plant traits, subsequently affecting spectral properties of plant functional types inhabiting specific microforms (Schaepman-Strub et al., 2009). Hollows are usually dominated by aquatic peat mosses and occasional graminoids and sedges, while lawns and hummocks are occupied by more dry-adapted peat moss species, as well as graminoids, lichens, and dwarf shrubs. Both microforms and their plant functional types occur at fine spatial scales varying from 1–10m to 0.01–1m, respectively (Belyea & Baird, 2006).

The spatial organization of microforms and plant functional types is a well-known indicator of peatland functions for multiple reasons. First, microforms affect the hydro-physical properties of a peatland (Branham & Strack, 2014; Waddington et al., 2010), hereby affecting water flow and nutrient dynamics (Eppinga et al., 2008; Macrae et al., 2013). Second, the spatial organization of microforms and their associated plant functional types strongly affect carbon sequestration through differences in productivity and decomposition (Aerts et al., 1999; Goud et al., 2017; Johnson & Damman, 1991; Laine et al., 2012; Turetsky et al., 2008). These differences are further amplified by the increasing ratio of methane to carbon-dioxide emissions through soil respiration along the water table gradient from hummock to hollow (Bubier et al., 1993; Krohn et al., 2017; Laine et al., 2007; Lunt et al., 2019). Third, there is evidence that retaining a diverse composition of plant communities through microform variations can increase the overall carbon sink function of a peatland (Robroek et al., 2017). Lastly, the presence of microform variations may facilitate reorganization under changing environmental conditions through lateral expansion and contraction (Belyea & Clymo, 2001), hereby leading to broader ecosystem resilience.

Given the importance of microforms and plant functional types in peatland functioning, as well as the spatial scales at which they occur, remote sensing with unmanned aerial vehicles (UAV) or drones has recently gained much attention for its potential role in mapping peatland vegetation. However, while peatland vegetation patterns have successfully been mapped in recent drone studies (Beyer et al., 2019; Bhatnagar et al., 2021; Palace et al., 2018; Räsänen, Aurela, et al., 2020; Räsänen & Virtanen, 2019; Steenvoorden et al., 2022), upscaling of this approach is hampered by the largely unknown interdependency between spatial resolution, spatial vegetation characteristics, and classification accuracy in different peatlands. More precise understanding of the relationship between these factors is required not only to shed light on the potential and limitations of using drones for large-scale mapping and monitoring of peatland vegetation patterns, but also those of aerial and satellite imagery.

In this study, we investigated the effect of various spatial resolutions of drone imagery on the classification accuracy and consistency of microforms and plant functional types in eight peatlands varying in the complexity and heterogeneity of their vegetation. We hypothesize that the minimum spatial resolution required for making accurate classifications of microforms and plant functional types 1) is located between 0.1 and 1m for all peatlands, and 2) is affected by the spatial characteristics of the vegetation itself (size, shape, configuration, and diversity), being smallest in peatlands with small, complex, finely distributed, and diverse vegetation patterns.

4.2 Materials & Methods

4.2.1 Study area

In this study, we investigated eight different Irish ombrotrophic peatlands representing a broad range in the composition and complexity of their vegetation patterns (Figure 4.1). Peatlands in Figure 4.1 are sorted visually from left to right and top to bottom in order of decreasing pattern complexity from smaller, complex, finely distributed and more diverse patches to larger, compacted, more clustered and less diverse patches. Bangor Erris and Roundstone are two Atlantic blanket bogs, which occur along the west-coast of Ireland under higher precipitation rates (usually >1200mm per year) than the other peatlands in our study. The central areas of these two peatlands exhibit a clear hummock-lawn-hollow pattern, but where Bangor Erris has relatively large and clustered pools, those of Roundstone are more interspersed with lawns and hummocks (Figure 4.1). Besides, the two Atlantic blanket bogs contain notably less peat moss cover than the raised bogs in our study area. Carrowbehy is a western raised bog complex of which its central areas also exhibit a clear hummock-lawn-hollow pattern with relatively frequent open water pools and high peat moss cover. Derrinea is also a western raised bog with similar vegetation patterning as Carrowbehy, but with smaller open water pools and a flush system in its central zone. Moyclare, Mongan, Ferbane, and Raheenmore are all Midland raised bogs, and exhibit less developed microtopography than the two western raised bogs, lacking permanent pools and extensive hollows. However, the vegetation patterns of the central areas of Raheenmore are even more homogeneous than the other peatlands, missing noteworthy hollows and being dominated largely by hummocks interspersed with lawns filled with graminoids and only some peat mosses.

All peatlands are part of Irelands’ Special Areas of Conservation network under the EU Habitats Directive (92/43/EE; Mackin et al., 2017; National Parks and Wildlife Service, 2018). Carrowbehy, Mongan, and Raheenmore have undergone hydrological restoration with drain blocking work (Fernandez et al., 2014), as far back as 1984 on Mongan and continuing intermittently on the four sites. However, all peatlands were subject to active EU-funded restoration measures through LIFE (L’Instrument Financier pour l’Environment program). Specifically, all six raised bogs received restoration between 2016 and 2022 through the “The Living Bog” restoration project (LIFE code: LIFE14 NAT/IE/000032). The blanket bogs included in this study have been under activate conservation since 2021 through the “Wild Atlantic Nature” restoration project (LIFE code: LIFE18 IPE/IE/000002).

4.2.2 Drone imagery capture

We retrieved drone imagery from the central and hydrologically most intact areas of all peatlands during two different field seasons (2021 and 2022) using a DJI Mavic 2 Pro drone with Hasselblad L1D-20c red–green–blue (RGB) colour sensor camera, which contains a one-inch (2.54cm) CMOS sensor that captures images of 20 MP. Drone imagery of Roundstone, Bangor Erris, Carrowbehy, and Raheenmore was collected between 11 and 21 September 2021, respectively, while drone imagery of Moyclare, Mongan, Derrinea, and Ferbane was retrieved in the same month one year later between 6 and 14 September 2022, respectively. In 2021, we used DJI Ground Station Pro to design automated flights of about 2ha at an altitude of both 40m (1cm pixel size) and 120m (2.7cm pixel size) above ground level. We chose a flight altitude of 120m because it is the most efficient legal flight altitude to map fine-scale vegetation patterns in Irish peatlands (Steenvoorden et al., 2023). The higher spatial resolution imagery at 40m flight altitude was used to validate vegetation classes during development of training/testing samples used in classification (see also 2.2.4). To allow for georeferencing of the stitched drone imagery, we distributed four large 30 × 40cm ground control points around the edges of each 2ha plot and measured their position using a Topcon HiPer HR real-time kinematic (RTK) and TopNET+ global navigation satellite system (GNSS) with 1–3cm accuracy. For the flights in 2022, we did not use any ground control points because we designed automated flights of the whole peatlands, and used reference maps by ESRI in ArcGIS Pro for georeferencing.

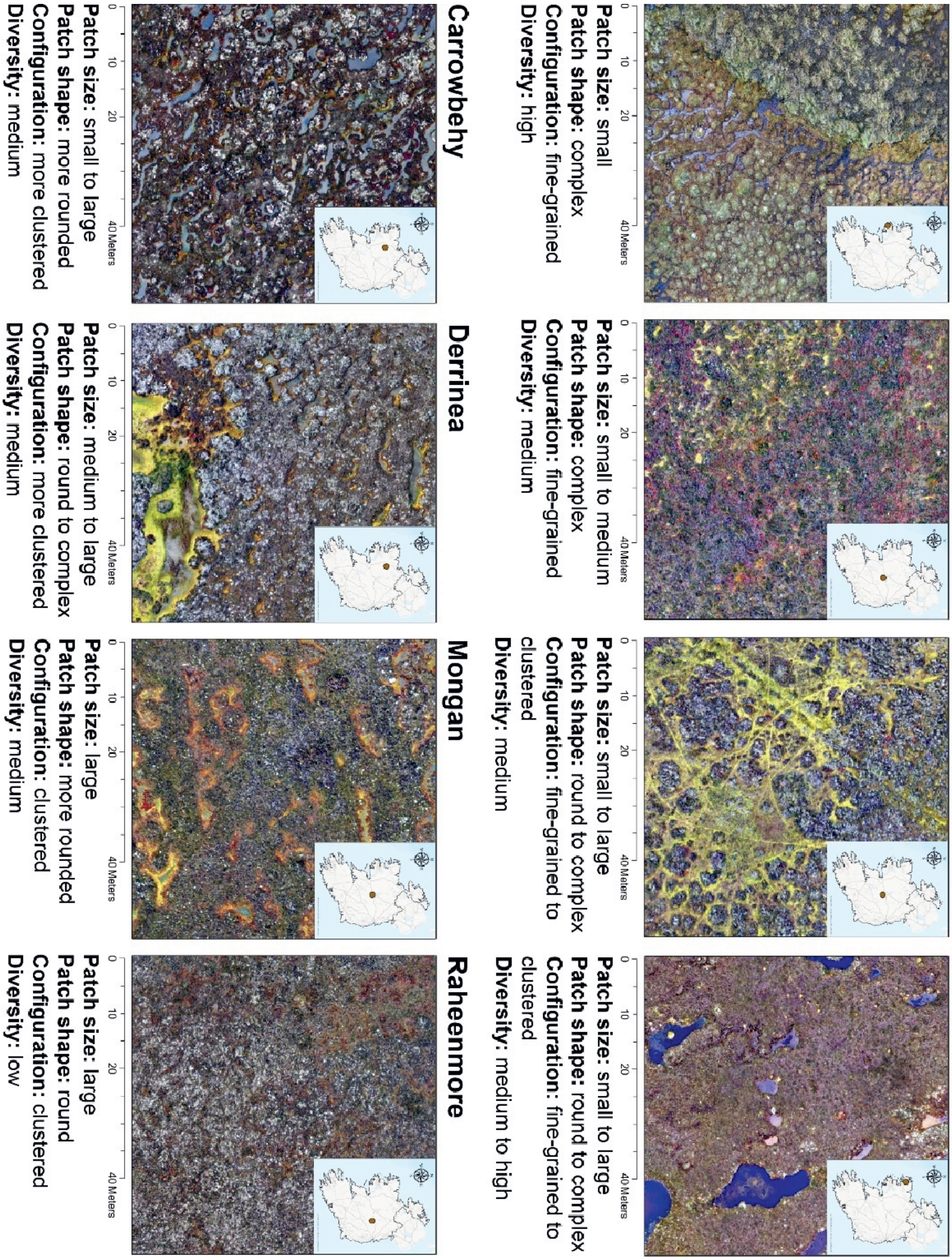

Figure 4.1 Study area maps showing the characteristic vegetation patterns in the central area of each of the eight Irish ombrotrophic peatlands that were investigated in this study as seen from a drone-derived true-colour orthomosaic at 120m altitude.

We used a forward/side image overlap of 80/80% for automated flights in 2021 and 75/60% forward/side image overlap for automated flights of peatlands in 2022, where the image overlap refers to the number of shared pixels between adjacent images, allowing for more accurate stitching and 3D reconstruction. We decided upon using less image overlap for all drone flights in 2022 because tests using different image overlap (75/60% versus 80/80%) in Carrowbehy in 2021 did not show differences in the accuracy of photogrammetry products, but notably improved flight and image-processing efficiency. All flights were conducted within one hour of solar noon and under fully cloudy to mostly cloudy weather conditions to minimize the potential effect of shade and light variability during classification. Wind speeds during all drone flights varied between low to moderate wind speeds up to 19 km/h.

4.2.3 Pre-processing drone imagery

We pre-processed all drone imagery products before classifying both microforms and plant functional types within each peatland. First, we used ortho-mapping software in ArcGIS Pro to produce a stitched RGB-orthomosaic of the drone images for each flight (2.7cm pixel size), as well as to create a Digital Terrain Model (DTM) with the same spatial resolution using the photogrammetric data contained within each individual drone image. Hereafter, we clipped a rectangular 1ha polygon from each full orthomosaic and DTM for use in all further analyses. Second, we grouped all pixels in each stitched orthomosaic into segments using a mean-shift clustering algorithm. This algorithm groups pixels based on similarity in spectral characteristics (spectral reflectance values) and spatial characteristics (proximity between pixels with similar reflectance) within the raster image. During segmentation, we used a minimum segment size of 0.25m because it has previously shown to be a cutoff point that yields significantly more efficient classifications than finer segmentation scales (Steenvoorden et al., 2023), once the pixel size of the drone imagery became larger than 0.25m (see also 2.6.), the segment size for a specific classification was automatically set to the spatial resolution of the imagery. Third, we detrended each DTM by fitting a second-order polynomial function through the elevation points in the DTM, and subsequently subtracted the DTM from the fitted trend function to correct for doming effects. Consequently, the detrended DTM represents the relative microtopographical differences in the orthomosaic more realistically, making it functional as an additional predictor variable during classification of both vegetation patterns (Steenvoorden et al., 2023). Lastly, we calculated Hue–Saturation–Value (HSV) colour model values and 10 RGB-derived vegetation colour indices as additional predictor variables to further emphasize spectral differences between vegetation classes of microforms and plant functional types. When using only individual RGB bands, the dark shades of different colours tended to be more spectrally similar than the same colour with different brightness, reducing classification accuracy. In contrast, the hue values of pixels with the same colour were more spectrally similar regardless of their brightness, diminishing potential effects of shade on spectral reflectance, increasing classification accuracy. Ultimately, we used a total of 25 predictor variables in classification of microforms and plant functional types, consisting of mean and standard deviation of RGB values, topography (minimum, maximum and mean elevation), mean of the HSV colour model values, 10 vegetation colour indices combining two or more RGB bands, and three shape metrics (pixel count, rectangularity, and compactness), computed separately for all segments in each orthomosaic (see also Table S4.1).

4.2.4 Ground truth data

We divided vegetation into microforms and plant functional types, which are two commonly used mapping units for vegetation patterns in peatlands. We then subdivided each mapping unit into multiple vegetation classes based on drone-visible indicator species (or the lack thereof) and their commonly associated position along the microtopographical gradient as seen from the newly developed orthomosaics. Microforms were subdivided into three classes: 1) hollow, 2) lawn, and 3) hummock (Table S4.3), while plant functional types were subdivided into five classes: 1) peat moss, 2) shrub, 3) graminoid, 4) lichen, and 5) water/bare peat (Table S4.3). Although water/bare peat is not officially a type of vegetation, we included it as a vegetation class in our analysis for plant functional types because it had noteworthy cover in most peatlands.

To classify microforms, we first created 500 randomly placed points within each orthomosaic and used the orthomosaic at 40m altitude as a reference dataset to validate the created training/testing samples for use in classification. This led to approximate area-proportional allocation of our training/testing samples. For classification of plant functional types, we used a targeted sampling approach instead with equal allocation, where we placed 100 points per plant functional type per orthomosaic at 120m flight altitude to prevent underrepresentation of uncommon plant functional types within each peatland. We used a total of 500 sampling points per mapping unit because a previous study on mapping the same peatland vegetation types showed by means of a sensitivity analysis that consistent classifications (>90%) are still retrieved even when only about 200–250 points of the total training/testing sample remained. By keeping the number of sampling points to 500 in this study, we made certain to capture all variation within each orthomosaic. To ensure all plant functional types were sampled across the whole orthomosaic, we created a 10×10 fishnet grid over each orthomosaic and took one sample per plant functional type from each sub-grid. However, some peatlands contained less than 100 individual samples for specific vegetation classes. In such cases, we used all available samples as training/testing samples for those vegetation classes. Because relative proportions of microforms differed among peatlands, and not all microforms and plant functional types were present or widely distributed within a peatland, the final allocation of training/testing samples differed per peatland for some vegetation classes. In the end, the number of training/testing samples ranged between 0 and 132, 62 and 171, and 197 and 375 for hollow, lawn, and hummock, respectively, and between 63 and 100, 25 and 100, and 0 and 100 for peat moss, lichen, and water/bare peat, respectively (Table S4.2). The vegetation classes shrub and graminoid contained 100 individual training/testing samples for all peatlands.

4.2.5 Vegetation classification

We classified the vegetation of each mapping unit for each orthomosaic using the ensemble classifier Random Forest (RF; Breiman, 2001) in Python's Scikit-learn module (Pedregosa et al., 2011). Here, we employed the 25 predictor variables at each spatial resolution as input datasets (see also 2.6), using selected segments from the training/testing dataset. Hereafter, we split the training/testing samples of each orthomosaic using five-fold stratified cross-validation (analogous to a ratio of 80/20 for training/testing). We chose this cross-validation approach because it minimized variance of model performance in our study as compared to repeated K-Fold cross-validation or a larger number of folds (Jiang & Wang, 2017). Classification performance per vegetation class and final classification performance of each orthomosaic were computed by averaging precision, recall, and F1-score over all folds in the RF model using the testing samples. We averaged classification performance over all folds to reduce potential variability related to the specific samples chosen for training/testing in each fold, hereby providing a more consistent and generalizable evaluation of the overall performance of the RF model. Besides, we used F1-score as preferred classification error metric because it is more robust to imbalanced training/testing datasets, as was often the case in our study (Table S4.2). An average F1-score of 1 indicates a perfect prediction, while any value in between 0 and 1 (or 0–100%) indicates the probability that a testing sample is correctly classified. We classified all segments within each orthomosaic by taking the most frequently classified vegetation class for each segment over all folds.

4.2.6 Determining minimum spatial resolution

To assess the minimum spatial resolution required for mapping peatland vegetation, we first resampled the orthomosaic and DTM of each peatland at 120m flight altitude in 20 increments from 2.7cm to 1m using the bilinear interpolation. This algorithm determines the new value of a cell based on a weighted distance average of the four nearest input cell centres. After resampling, we performed a sensitivity analysis by iteratively classifying both microforms and plant functional types for all peatlands using each combination of resampled drone imagery products. We then determined the minimum spatial resolution required to achieve consistent classifications for each mapping unit and for each peatland by averaging overall classification accuracy over all folds in each RF model. Minimum spatial resolution was reached once averaged overall classification accuracy of the next (coarser) spatial resolution became lower than 90%. To validate the use of the 90% overall classification accuracy limit in determining minimum spatial resolution, we used stratified estimation (Olofsson et al., 2013) to doublecheck to what extent 90% classification accuracy corresponded with expected 10% uncertainty in mapped area over all vegetation classes as derived from the confusion matrix. Stratified estimation uses both the confusion matrix and mapped class areas (m^2) from a classification to compute the effect of misclassifications on estimated areas of each class. This represents uncertainty in mapped areas due to misclassifications more realistically, because solely using sample counts from the confusion matrix tends to underestimate or overestimate the true estimated area of vegetation classes, especially when their areas in the field are variable (Olofsson et al., 2014). While calculation of uncertainty through stratified estimation showed that studied peatlands had slightly higher uncertainty in estimated areas than 10% for both mapping units (12.4% ± 3.0% and 12.4% ± 5.2% for microforms and plant functional types, respectively; Figure S4.5, S4.6), both average uncertainty and their confidence intervals suggest that using a classification accuracy of 90% leads to relatively uniform uncertainty estimates over all studied peatlands, validating its use as a cutoff value.

4.2.7 Spatial patch characteristics

To evaluate the role of the vegetation patterning of microforms and plant functional types on their minimum required spatial resolution, we created ordinary least squares univariate linear regression models using the Python package Statsmodels version 0.14.0 (Seabold & Perktold, 2010). We used the computed overall minimum spatial resolution for each mapping unit from all peatlands as response variable and used five spatial patch metrics as predictor variables: 1) “mean area” (patch size), 2) “standard deviation of area” (patch size), 3) “landscape shape index” (patch shape; Patton, 1975) 4) “conditional entropy” (patch configuration; Nowosad & Stepinski, 2019), and 5) “Shannon diversity index” (patch diversity; Figure 4.2; Shannon, 1948). These metrics were selected from a total of 22 main metrics available in the Python package PyLandStats version 2.4.2 (Bosch, 2019; excluding the six distribution-statistics metrics available per landscape metric) based on their recognized use in describing and quantifying the spatial organization of patterns on a landscape scale. To compute each spatial patch characteristic, we used the classified images of microforms and plant functional types with the highest spatial resolution of 2.7cm. We employed the highest spatial resolution maps because these most realistically reflected the real patchiness of the vegetation, and because computation of spatial vegetation characteristics using coarser resolution imagery leads to notable loss of spatial patch complexity (Räsänen & Virtanen, 2019; Virtanen & Ek, 2014).

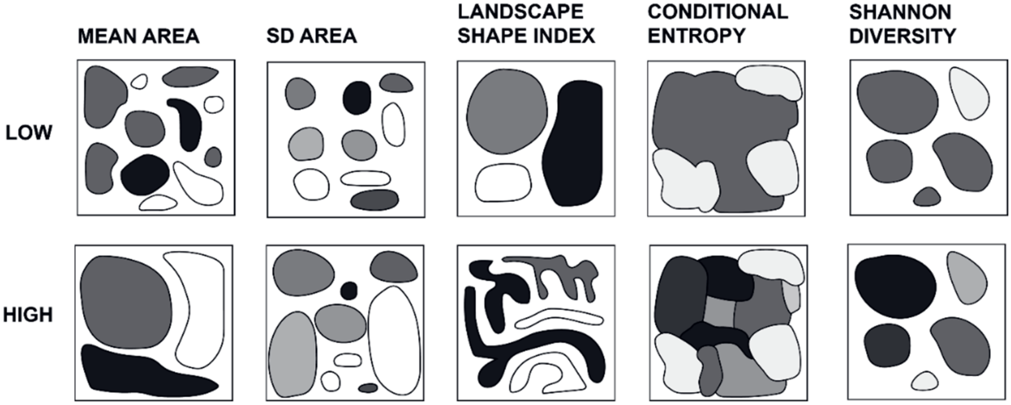

Figure 4.2 Visualization of the spatial patch metrics used in ordinary least square regression models to evaluate the role of spatial vegetation characteristics on the minimum image resolution requirements for mapping microforms and plant functional types. Presented are a hypothetical “low” and “high” values for mean area (patch size) standard deviation (SD) of mean area (patch size), landscape shape index (patch shape), conditional entropy (patch configuration), and Shannon diversity (patch diversity).

4.3 Results

4.3.1 Minimum spatial resolution requirements

4.3.1.1 Microform classifications

Microform classifications showed consistently high accuracies (>90%) for all peatlands until a spatial resolution of 0.5m ± 0.2m on average. However, variation in the minimum required spatial resolution between peatlands ranged from 0.25 m in Roundstone to 0.7m in Mongan (Figure 4.3; Figure S4.1). Minimum required spatial resolution indeed also strongly differed between different microform classes (Figure 4.5). For example, hummock had a minimum required spatial resolution of 0.65m ± 0.2m on average. In the case of Mongan, hummock was even consistently classified up until the coarsest spatial resolution of 1.0m. Conversely, lawn and hollow had, respectively, ranged in minimum required spatial resolution between 0.20 and 0.55m and 0.25 and 0.75m. This was expected, because lawn and hollow in Irish peatlands are smaller and more elongated than hummocks. The variation in minimum required spatial resolution between microform classes coincided with their frequency of occurrence, hummock being the dominant microform in all peatlands (Figure S4.7).

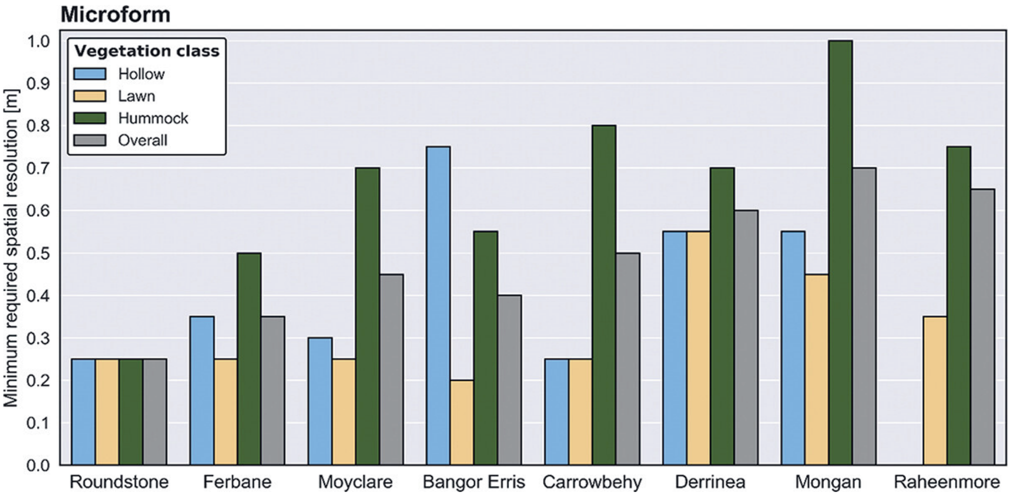

Figure 4.3 Bar graphs visualizing the minimum required spatial resolution for consistent mapping of microform vegetation classes for each of the eight studied peatlands. “Overall” represents the average over all vegetation classes. Raheenmore is missing a bar for hollow because it was not present in the peatland.

4.3.1.2 Plant functional type classifications

Plant functional type classifications showed consistently high accuracies for all peatlands until a spatial resolution of 0.25m ± 0.1m on average (Figure 4.5), which is twice as detailed as those for microforms. Overall minimum spatial resolution for plant functional types varied notably less between peatlands than for microforms, ranging from 0.15m in Moyclare to 0.35m in Carrowbehy (Figure 4.4; Table S4.4). Like microforms, minimum required spatial resolutions for plant functional types varied strongly between vegetation classes. For instance, while peat moss was well classified up until 0.45m ± 0.2m spatial resolution (Figure 4.5) and ranged from 0.15 to 0.65 m, other plant functional types like shrub, graminoid, and lichen had notably higher minimum spatial resolution requirements between 0.15 and 0.30m (Table S4.4). Water/bare peat had the coarsest required spatial resolutions of all plant functional types (Table S4.4), which can likely be attributed to the relatively large open water pools that were present in many of the studied peatlands (Figure S4.8). Nevertheless, the variation in minimum required spatial resolution between vegetation classes was only partly aligned with their occurrence frequency as shrub and graminoid were by far the most occurring plant functional types in all peatlands, followed by peat moss, lichen, and water/bare peat (Figure S4.4; Figure S4.8).

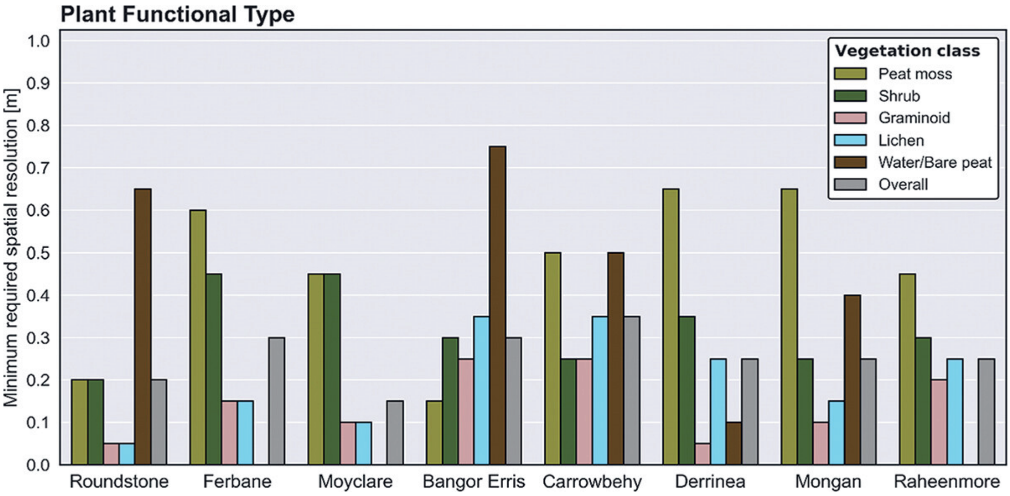

Figure 4.4 Bar graphs visualizing the minimum required spatial resolution for consistent mapping of plant functional type vegetation classes for each of the eight studied peatlands. “Overall” represents the average over all vegetation classes.

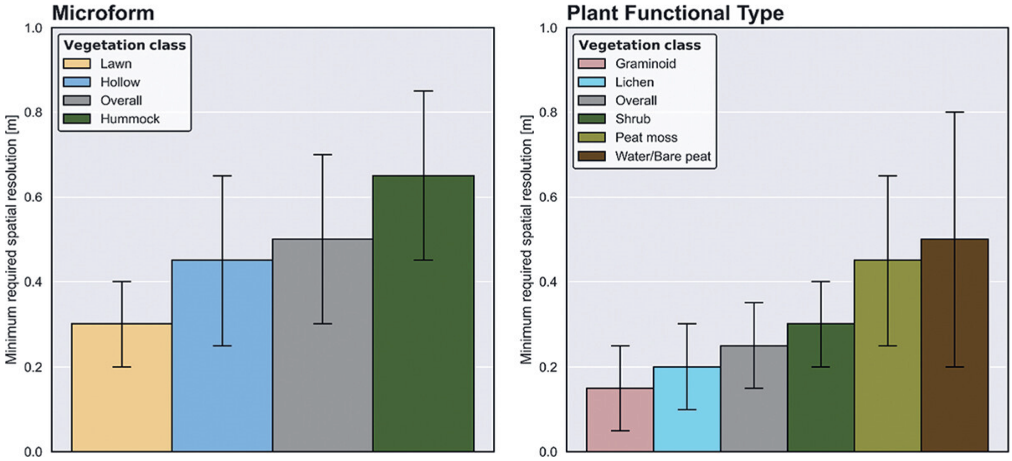

Figure 4.5 Bar graphs visualizing the minimum required spatial resolutions for consistent classification of the studied mapping units: microform (left) and plant functional type (right). “Overall” represents the average over all vegetation classes within a mapping unit. Error bars represent standard deviation of minimum required spatial resolution over all eight peatlands.

4.3.2 The role of spatial patch characteristics

4.3.2.1 Microform characteristics

For microform classifications, the minimum spatial resolution per peatland was strongly related to the spatial organization of the microforms (Figure 4.6). We found strongly significant linear relationships ($R^2 > 0.7$, $p < 0.05$) between minimum spatial resolution and all spatial patch metrics, except for the Shannon diversity index, which showed a weak relationship. Specifically, minimum required spatial resolution decreased with an increase in mean and standard deviation of patch area (Figure 4.6; Table S4.5), suggesting that that coarser spatial resolution imagery can be used for mapping peatlands with larger microform patches and lower variability in microform patch area than those with smaller and more variable microform patches. Also, minimum required spatial resolution showed a strong negative relationship with the landscape shape index and conditional entropy (Figure 4.6; Table S4.5), indicating that peatlands with more compact, round, and clustered microform configuration such as Mongan, Raheenmore and Derrinea can be classified consistently using imagery with coarser spatial resolutions than peatlands with less organized patch forms. Lastly, the Shannon diversity index showed only a moderate relationship with the minimum required spatial resolution of microforms (Table S4.5). This suggests that the minimum required spatial resolution for mapping microforms is less sensitive to variation in landscape-scale diversity and evenness than their size and shape metrics.

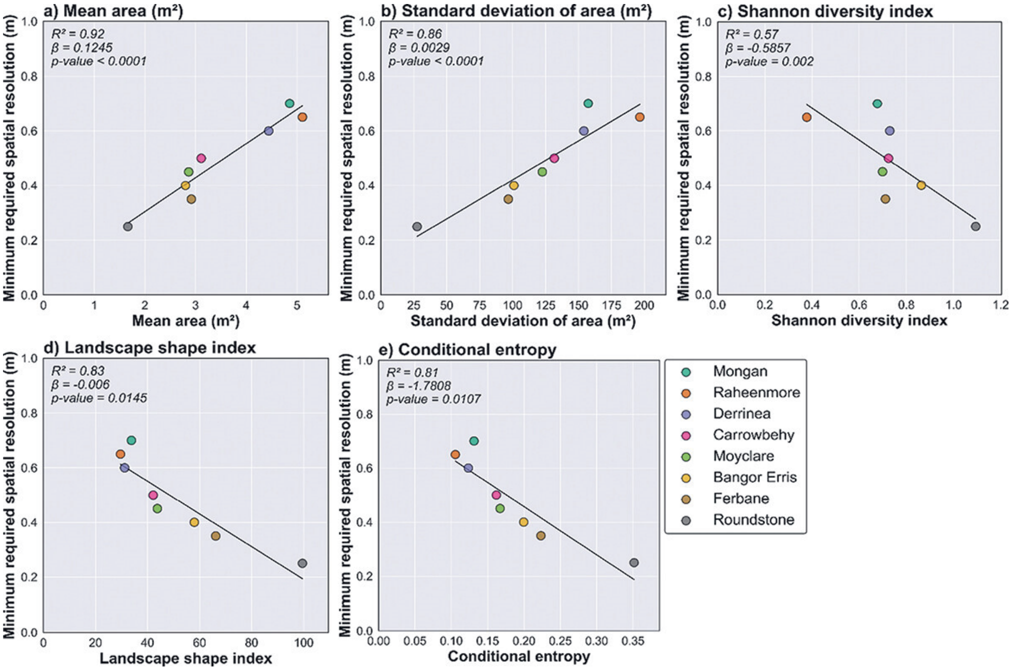

Figure 4.6 Ordinary least squares univariate regression lines for models assessing the relationship between spatial patch metrics and minimum required spatial resolution for microforms. a) Mean area ($\beta = 0.1245$, R2 = 0.92, $p < 0.0001$), b) standard deviation of area ($\beta = 0.0029$, R2 = 0.86, $p < 0.0001$), c) Shannon diversity index ($\beta = -0.5857$, R2 = 0.57, $p < 0.0020$), d) landscape shape index ($\beta = -0.0060$, R2 = 0.83, $p < 0.0145$), and e) conditional entropy ($\beta = -1.7808$, R2 = 0.81, $p < 0.0107$). Legend with peatland data points is sorted by minimum required spatial resolution in descending order.

4.3.2.2 Plant functional type characteristics

In contrast with microforms, minimum spatial resolution requirements for plant functional types were unaffected by their spatial vegetation characteristics (Figure 4.7). Where microforms had strong linear relationships with four out of five of the computed spatial vegetation characteristics, minimum spatial resolution of plant functional types had only a weak negative relationship with mean patch area (Figure 4.7; Table S4.5). However, this negative relationship indicates that mapping plant functional types with a higher mean patch area requires imagery with lower pixel size, and plant functional types with a small mean patch area require imagery with a high pixel size.

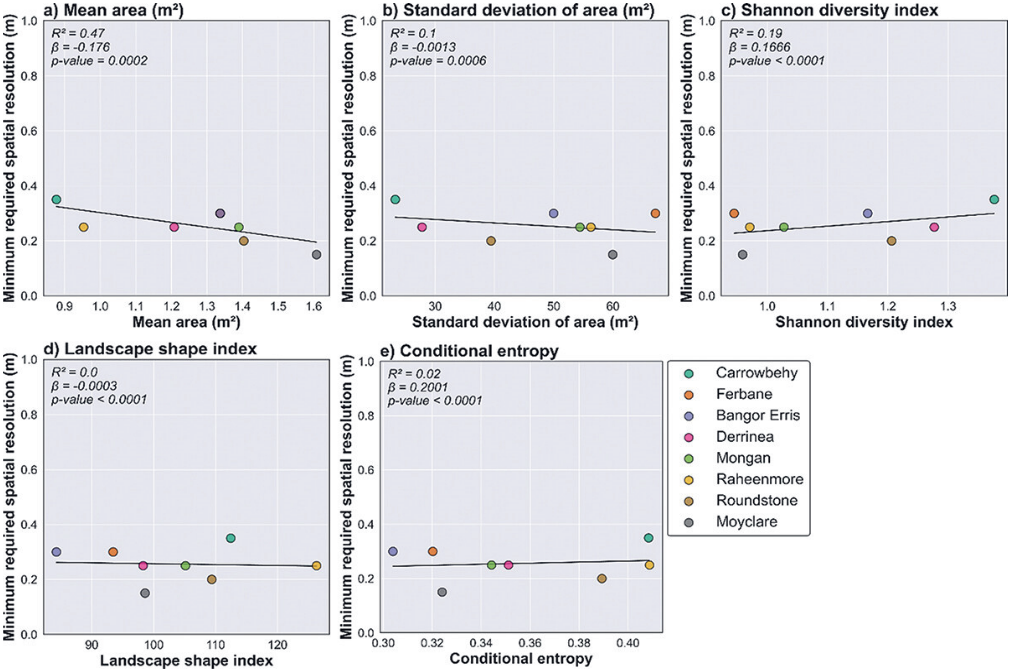

Figure 4.7 Ordinary least squares univariate regression lines for models assessing the relationship between spatial patch metrics and minimum required spatial resolution for plant functional types. a) Mean area ($\beta = -0.1760$, $R^2 = 0.47$, $p < 0.0013$), b) standard deviation of area ($\beta = -0.0013$, $R^2 = 0.10$, $p < 0.0006$), c) Shannon diversity index ($\beta = 0.1666$, $R^2 = 0.19$, $p < 0.0001$), d) landscape shape index ($\beta = -0.0003$, $R^2 = 0.00$, $p < 0.0001$), and e) conditional entropy ($\beta = 0.2001$, $R^2 = 0.02$, $p < 0.0001$). Legend with peatland data points is sorted by minimum required spatial resolution in ascending order. Please note that the x-axis of all subplots (a–e) in this graph has not been normalized and does not include a zero value for each spatial patch characteristic. This was done because the range in values for each spatial patch characteristic was so small that the graph would lose visual clarity.

4.4 Discussion

4.4.1 The relationship between spatial resolution requirements and vegetation patterning

4.4.1.1 Differences between vegetation mapping units

We found that microforms can be classified and mapped with coarser spatial resolution imagery than plant functional types (0.5m versus 0.25m on average, respectively), likely because of their larger and more variable size, shape, and configuration than the individual plant functional types of which they are composed. Indeed, shrub, lichen, and graminoid had among the same spatial resolution requirements with low variability (Figure 4.5; Table S4.4). Nevertheless, some specific plant functional types such as peat moss and water/bare peat were consistently classified well until spatial resolutions were reached that were similar to the overall minimum required spatial resolution for microforms. The overall high minimum required spatial resolutions for peat moss (0.45m) compared to other plant functional types is explained by its carpet-like growth form in both lawns and hummocks (van Breemen, 1995; Waddington et al., 2015). Besides, peat mosses are often well distinguished because their spectral signature differs markedly from other plant functional types (Bubier et al., 1997; Harris & Bryant, 2009; McPartland et al., 2019; Schaepman-Strub et al., 2009). The blanket bogs in our study required higher spatial resolutions to classify peat mosses than the raised bogs (Figure 4.4), which resulted from the fact that blanket bogs have lower and more dispersed peat moss cover than raised bogs. Lastly, open water pools were also consistently classified well with coarser spatial resolutions than other plant functional types (0.5m), which we attribute to the large open water pools in some peatlands such as Bangor Erris and Carrowbehy. However, spatial resolution requirements for individual microforms were affected by the sampling strategy of our study. This is because area-proportional allocation of training/testing samples in combination with the structural dominance of hummocks in all studied peatlands, but Roundstone led to increased sensitivity for misclassifications of the less-occurring lawn and hollow (Table S4.2; Figure S4.3, S4.4).

4.4.2 The role of spatial patch characteristics

We show that spatial resolution requirements of microforms were not only determined by their corresponding vegetation types but also by their spatial characteristics: peatlands that exhibit larger, compacter, more clustered, and less diverse microforms could be mapped at coarser spatial resolution imagery (up to 0.7m) than peatlands with smaller and less organized microforms. This result has two main implications for mapping peatland functions through vegetation patterns: 1) a quick visual inspection of the size and organization of vegetation patterns may help to plan flight campaigns and subsequent analyses more efficiently, as reductions in resolution lead to notably quicker image capture and processing (Steenvoorden et al., 2023) and 2) as microform configurations may change with peatland condition (Steenvoorden et al., 2022), mapping efforts targeting changes in peatland functioning for example as a result of degradation through time or recovery since restoration, should be adapted to the condition demanding the highest spatial resolution.

In contrast to microforms, the spatial resolution requirements of plant functional types showed no significant relationships with spatial patch metrics for plant functional types, but only a weak negative relationship with mean patch area. However, the direction of this relationship suggests that more spatial detail is needed if patches become larger, which is in contrast with our second hypothesis and with our microform results. We attribute the lack of strength for these relationships to the lack of range in spatial patch metrics of plant functional types among peatlands in our study, which on average were approximately three times smaller than those of microforms (see also Figure 4.7). While we argue that the absolute range in spatial vegetation characteristics of plant functional types is much lower than those of microforms, we cannot exclude that the limited range in spatial characteristics in our study was an artifact of our purposeful sampling approach. We took care to minimize artifacts by systematically sampling a variety of patches per plant functional type throughout the whole peatland. We therefore believe the targeted sampling approach is not the main cause of the limited variation in spatial vegetation characteristics for plant functional types observed in our study. Based on these findings, we argue that spatial vegetation characteristics play a notable role in determining spatial resolution requirements for microforms, but not for plant functional types.

4.4.3 Implications for mapping, monitoring and upscaling

4.4.3.1 When to stick to drones for mapping peatland vegetation

On the one hand, our results show that drone imagery is probably not necessary to map all mapping units in heterogeneous landscapes like peatlands, because consistent classifications of specific vegetation classes were obtained in most peatlands using spatial resolutions that parallel those of the highest spatial resolution aerial imagery and pan-sharpened imagery of some commercial satellites, which is about 0.3 m. On the other hand, our study also suggests that the use of drones for mapping of fine-scale vegetation patterns and functions has several advantages over the use of aerial and satellite remote sensing. First, simply not all microforms and/or plant functional types occur at a spatial scale that is currently visible on aerial or even the highest spatial resolution pan-sharpened satellite imagery. Consequently, mapping vegetation patterns on a landscape-scale using aerial and satellite imagery may miss spatial heterogeneity in some peatlands, whereas they can be captured using drone imagery. Second, segmented patch boundaries at the highest spatial resolution imagery followed vegetation patterns in the field with remarkably higher accuracy than resampled imagery with spatial resolutions mimicking aerial and satellite imagery. Räsänen and Virtanen (2019) also found that spatial vegetation characteristics in peatlands were most complex when classifications were based on drone imagery segmentation. This increasing loss of spatial complexity at lower spatial resolutions is logical, because small patches of vegetation become aggregated into a rectangular pixel if spatial resolutions become coarser than the size of the vegetation class under investigation. This loss of spatial complexity may not be problematic if vegetation classes show adequate spectral differences with coarser spatial resolution imagery and/or if the spatial characteristics of vegetation are not the object of study. However, accurate information on spatial vegetation characteristics may become important if studied vegetation classes are more spectrally similar or if different vegetation classes show notable spatial variability in the landscape. For instance, hummocks are generally large, round, and more compact, while lawns and hollows are often smaller and more elongated. Our results show that differences in these spatial patterns can currently only be captured using segmentation of drone imagery.

Third, collection and processing of high spatial and spectral resolution aerial imagery and lidar data are costly (Anderson & Gaston, 2013; Lovitt et al., 2017). This often leads to areas with missing spatial data or areas containing spatial data with low temporal resolution. In these cases, and given the added value of topographical data in classification of fine-scale peatland vegetation patterns (Räsänen, Aurela, et al., 2020; Steenvoorden et al., 2022), drones offer a far cheaper and flexible solution to consistently collect both multispectral and topographical data in many areas with limited extent. Besides, while we obtained consistent classifications of both microforms and plant functional types using our DJI Mavic 2 Pro with RGB camera sensor, several studies have shown the added value of a near-infrared (NIR) sensor on drones for discriminating different peatland vegetation types (Knoth et al., 2013; Räsänen, Aurela, et al., 2020). NIR imagery is also well-suited to separate vegetation from open water in peatlands because water tends to absorb NIR more than light in the visible spectrum. This can be especially valuable if open water pools are already partially filled in with vegetation, like in some of our studied peatlands. Consequently, the inclusion of NIR sensors in classification of microforms and plant functional types could reduce spatial resolution requirements of some vegetation classes that are sensitive to changes in NIR, like hollow, lawn and peat moss. Because NIR sensors are becoming increasingly available and affordable on consumer-grade drones, we recommend their inclusion for future studies investigating vegetation patterns in peatlands where possible.

Fourth, plant phenology is important in peatlands both because it indirectly affects the identification and differentiation of specific vegetation patterns (Cole et al., 2014), but also because it directly affects peatland carbon fluxes (Antala et al., 2022; Koebsch et al., 2020; Kross et al., 2014). While multispectral satellite imagery has shown potential for broadly capturing peatland phenology across the growing season (Arroyo-Mora et al., 2018; Linkosalmi et al., 2022), this type of data may not be available during time-periods of the year where phenological stages of plants are most optimal for their characterization. Synthetic Aperture Radar (SAR) could be valuable here as it can reach spatial resolutions of 1m, can penetrate vegetation canopies, is sensitive to water and vegetation structure, and has the capacity to retrieve imagery in all weather conditions. However, the potential of SAR in discriminating fine-scale vegetation phenology has to our knowledge not yet been studied in peatlands. Besides, our results suggest that the ability to reliably determine the different phenological stages of microforms and plant functional types throughout a peatland may require imagery on finer spatial and/or temporal scales than both multispectral and radar satellite imagery can currently provide. The flexibility and spatial resolution of drone imagery thus proves an invaluable tool for mapping at ecosystem to landscape scales. Nevertheless, it should be noted that drones can also be limited by extreme weather conditions occurring in peatland areas during some time-periods of the year, including high wind, fog, rain, heat, and cold.

The maximum spatial scale at which drone imagery analyses could still be considered the most efficient approach over aerial or satellite imagery is obviously unclear and dependent on many factors, including the study area, the chosen drone, and flight and image-processing parameters. However, using our chosen flight parameters of 120m flight altitude and 75/60% forward/side overlap, it most certainly reaches extents of up to 1000 hectares because our DJI Mavic 2 Pro could fly areas of about 265ha per hour. This means an area of about 1000 hectares can theoretically be flown within 1.5 hours of solar noon on the same day using most consumer-grade drones.

4.4.3.2 Transitioning to aerial and satellite imagery

The decision or necessity of transitioning from drone to aerial and/or satellite imagery when mapping and monitoring peatland vegetation patterns is affected by the scale of the study area, spatial characteristics and spectral separability of the peatland vegetation pattern under investigation, and the research goal. Spatial resolution requirements are lower in cases where the relative proportions of vegetation patterns within peatlands only need to be categorized broadly and there is no need to maximize classifier performance for all vegetation classes, or if peatlands are dominated by only few vegetation classes that are easy to detect. If the goal is to evaluate the role of vegetation as ecological indicators for broader ecosystem functioning, one could use remote sensing platforms with a spatial resolution equal or higher than the overall minimum required spatial resolution for that specific vegetation class. When using satellite imagery, one could exploit the fact that most Earth observation satellite missions with freely available imagery like Landsat and Sentinel-2 carry multispectral sensors with NIR and Shortwave Infrared (SWIR), which are of particular added value in discriminating important peatland vegetation classes like peat mosses, as well as open water (Bhatnagar et al., 2021; Bhatnagar, Gill, Regan, et al., 2020; A. Harris & Bryant, 2009a; Krankina et al., 2008). In contrast, when vegetation maps of individual peatlands are linked to their biogeochemical cycles such as carbon fluxes, the relative proportions of all existing vegetation classes need to be calculated with high accuracy because different microforms and their associated plant functional types often have markedly contrasting rates of carbon accumulation and decomposition (Loisel & Yu, 2013b; Lunt et al., 2019; Riutta et al., 2007; Strack, Waddington, et al., 2006; Waddington & Roulet, 1996). When fluxes are related to maps of plant functional types or plant phenology, one would need drone imagery, but when fluxes are coupled to microforms, aerial imagery and very-high resolution satellite imagery (~0.3m) can be sufficient.

Given the large, isolated, and inaccessible nature of many peatlands, upscaling of remote sensing analyses in these ecosystems will require methods that combine the strengths of consumer-grade drones (e.g. potential for high spatio-temporal resolution, flexibility) with those of aerial and satellite remote sensing (e.g. regional and global coverage, multiple sensors). Drones could be used here to train, test, validate, and calibrate coarser spatial resolution but larger-scale commercial aerial and satellite imagery (Bhatnagar et al., 2021; Riihimäki et al., 2019). While some recent studies show the added value of so-called nested drone-aerial or drone-satellite mapping approaches in peatlands (Bhatnagar et al., 2021; Carless et al., 2019; Connolly et al., 2007; Räsänen & Virtanen, 2019), consistent development of these methodologies is only just emerging. Besides, although some of these nested drone-aerial or drone-satellite mapping approaches may require some radiometric calibration, we justify the use of resampled drone imagery as a proxy for aerial and satellite imagery because RGB reflectance values and vegetation indices using NIR between both remote sensing platforms often have very high correlation (Assmann et al., 2020; Fawcett et al., 2020; Jiang et al., 2022; Padró et al., 2018).

4.5 Conclusion

Our study shows that minimum required spatial resolutions for mapping peatland microforms and plant functional types range from 0.1 to 1m and are variable across peatlands as well as between mapping units and their individual vegetation classes. We also found that spatial vegetation characteristics were important drivers of minimum spatial resolution for microforms, but not for plant functional types, which required imagery of at least 0.25m spatial resolution in all peatlands on average. Based on these findings, we conclude that spatial vegetation characteristics strongly affect upscaling of peatland vegetation mapping beyond the landscape scale by constraining the use of specific remote sensing platforms.

Chapter 5

Towards standardised large-scale monitoring of peatland habitats through fine-scale drone-derived vegetation mapping

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Abstract

1. Northern peatlands provide key climate regulating services by sequestering and storing atmospheric carbon as peat, but also provide habitat for specialised plant and animal species. Ecosystem-wide monitoring of the functions associated with these services is necessary to better inform policy and management and facilitate carbon financing schemes. Mapping peatland vegetation as an ecological indicator of their functions using drones has proven promising herein, yet the absence of standardised methods limits implementation.

2. We developed drone-derived vegetation maps and compared them with two types of field-based ground-reference maps: 1) habitat distribution (ecotopes) and 2) habitat quality (status) for five Irish peatlands (35–124ha). We also explored spatial transferability of our mapping approach across peatlands. First, orthomosaics and digital terrain models (DTM) were derived from drone imagery, after which plant functional types and microforms were separately classified. Second, ecotope and status maps were classified using the proportions of the fine-scale vegetation and the range in DTM within 20x20m grid cells as input predictor variables.

3. Drone-derived ecotope and status maps captured the overall vegetation zonation of the conventional maps well, with the least mismatches for the peatlands displaying clear concentric zonation. Classification performance ranged between 88% for status and 72% for ecotope maps between peatlands. The lower classification performance for ecotopes was partly an artifact from gridding the conventional polygon-shaped ground-reference maps. Further classification errors resulted from artificial landscape features, variable plant phenology, and inaccuracies in the detrended DTM data at peatland-scale. Spatial transferability of the mapping approach was limited. Particularly, using pooled ground-reference data for classification decreased model performance with 5% for status and 10% for ecotope maps, largely because microform and plant functional type proportions associated with peatland habitat classes in the conventional maps varied between peatlands.

4. Our findings highlight that both fine-scale vegetation patterns and habitats can be classified consistently on the peatland-scale using drone-derived imagery products and machine learning classifications. Yet, status is currently mapped notably more accurately than ecotopes. Also, peatland-specific ground-reference data is required until the conventional vegetation classes are more standardised across a wider variety of peatlands and peatland types.

Keywords: peatlands, raised bogs, vegetation patterns, habitat, drones, ecological indicators

5.1 Introduction

Northern peatlands are wetlands that provide crucial ecosystem services, including habitat provisioning for specialised species and climate regulation by storing atmospheric carbon in peat. Indeed, while northern peatlands cover only about 2% of the Earth's surface (Xu et al., 2018), these ecosystems store between approximately 475–620Gt of soil carbon (Yu et al., 2010), equalling about 90% of the global peatland carbon pool (Yu, 2011), and more than one-third of all terrestrially stored soil carbon (Rydin & Jeglum, 2013). Nevertheless, it is estimated that about 50% of the present-day peatland expanse in the European Union is degraded (Tanneberger, Moen, et al., 2021), caused largely by anthropogenic disturbances in recent centuries such as peat extraction, overgrazing, drainage, commercial forestry, wind farms and fire (Swindles et al., 2019). Recent recognition of the importance of healthy peatlands for the perpetuation of their ecosystem services has resulted in large amounts of attention from policy makers and carbon financing schemes (Bonn et al., 2014; Tanneberger, Moen, et al., 2021). To understand the effect of restoration efforts and to account for related investments, the need for accurate and standardised mapping of peatland functioning and associated services has notably increased (Andersen et al., 2017; Minasny et al., 2023; Reed et al., 2022).

Peatland vegetation structure (composition, diversity, and spatial organisation) is a recognised ecological indicator for habitat diversity and carbon accumulation (Couwenberg et al., 2011; Dieleman et al., 2015; Regan et al., 2020; Robroek et al., 2017; Swenson et al., 2019). The potential for vegetation as an indicator for peatland functions is particularly strong in raised bogs, where strong eco-hydrological feedback mechanisms drive and sustain the characteristic vegetation patterning (Eppinga, Rietkerk, et al., 2009; Waddington et al., 2015). Vegetation in raised bogs is organised along microtopographic surface gradients called microforms. Microforms typically occur at fine spatial scales and range in size between 1–10m (Belyea & Baird, 2006), and span from open water pools where the peat surface is always below the water table, to wet hollows, moist lawns, and finally to hummocks where the peat surfaces can reach up to 50cm above the water table. Differences in water and nutrient availability along this microtopographical gradient create ecological niches for different plant species sharing adaptations to the same local conditions (Johnson et al., 2015; Rydin & Jeglum, 2013). Consequently, microforms typically represent a distinct set of species and/or plant functional groups that can be recognised as a coherent vegetation unit. Here, hummocks are mostly dominated by shrubs, lichen, graminoids and more drought-adapted peat moss species (bryophytes from the genus Sphagnum), while hollows contain aquatic peat moss species interspersed with sedges (Andrus et al., 1983; Robroek, Limpens, Breeuwer, & Schouten, 2007; Rydin & Jeglum, 2013; Rydin & McDonald, 1985). Open water pools generally contain limited vegetation but sometimes harbour aquatic plant species (Schouten, 1984). Lawns are typical transition zones between hummocks and hollows, containing more intermediately drought-adapted peat moss species, occasionally interspersed with some shrubs, sedges, and forbs.

At the landscape scale, microforms and their associated plant functional types usually appear across raised bogs in regular vegetation complexes with spatial patterns of varying microform proportions, hereby forming characteristic peatland habitats also called ecotopes. These habitats reflect environmental conditions in different sections of a raised bog, such as water level, nutrient supply, drainage, and surface inclination (Schouten, 2002). Flat parts usually occur in the peatland centre, and often contain extensive areas with distinct microtopographical gradients ranging from high hummocks to open water pools. Moving from the flat centre towards the sloping marginal sections of a peatland, microtopography becomes less distinct, and habitats mostly contain only hummocks and lawns, as well as plant functional types associated with drier surface conditions. However, the extent and distribution of specific habitats do not invariably follow a concentric (circularly zoned) pattern, and can occur in different sections of a peatland depending on local hydrological conditions. Taken together, the spatiotemporal dynamics of peatland habitats can be used as an indicator of changes in peatland-wide environmental condition.

Given the strong relationship between vegetation structure and peatland functions, monitoring approaches for restoration often use the spatiotemporal dynamics of their vegetation patterns as an indicator for changes. While some of these approaches are carried out manually through field-based measurements, this is not always a feasible option because peatlands are generally large, isolated, inaccessible, and sensitive ecosystems. As a result, remote sensing with unmanned aerial vehicles (UAVs) or drones has recently gained much attention for its potential role in monitoring peatland vegetation dynamics. Particularly, drones can capture and process very-high-resolution (<0.05m) spectral, spatial, and topographical data with low cost and relatively high efficiency and flexibility (Steenvoorden et al., 2023; Steenvoorden & Limpens, 2023), all of which are important in characterising peatland vegetation patterns. These factors facilitate high repeatability of mapping efforts, which will invariably improve spatiotemporal resolutions of vegetation pattern maps. This could make drones an ideal bridge between field-based measurements and satellite remote sensing at least for monitoring intermediately large peatlands. Several recent studies have mapped peatland habitats using drone imagery (Bhatnagar et al., 2021; Bhatnagar, Gill, & Ghosh, 2020; Räsänen et al., 2019), illustrating the potential of the approach.

In this study, we sought to further optimize and standardise drone-based mapping of peatland habitats on the peatland-scale. We expected that 1) accurate maps of microforms and plant functional types could be derived at the peatland-scale, 2) the maps of plant functional types and microforms could be used to derive accurate ecotope and status maps, and 3) the habitat classification models would be spatially transferable among the same peatland type. We tested these expectations for five Irish raised bogs (35–124ha) representing a range in eco-hydrological integrity and compared them with field-based ground-reference maps by the Irish National Parks and Wildlife Service. We also explored spatial transferability of this mapping approach across peatlands by carrying out classifications with both peatland-specific (singular) and pooled ground-reference datasets.

5.2 Materials and methods

5.2.1 Study area

In Ireland, peatlands cover up to 21% of the landscape (Connolly, 2018), and occur across a broad climatological gradient of temperature, precipitation, and elevation. In this study, we investigated five Irish raised bogs distributed throughout the country (Figure 5.1; Table 5.1). We selected these raised bogs based on their contrasting level of eco-hydrological integrity and associated range in ecosystem functioning. The studied peatlands ranged from relatively intact with diverse habitat conditions and a corresponding high area of carbon accumulating habitats (see 5.2.1), to mostly degraded with lower habitat diversity and lower capacity for carbon accumulation. Eco-hydrological integrity of the studied peatlands was assessed by the Irish National Parks and Wildlife Service (NPWS) using so-called Favourable Reference Values (FRV). FRV as defined by the European Union (EU) Habitats Directive 92/43/EEC refer to a set of specific and measurable ecological conditions or parameters that serve as a benchmark from which the conservation status of habitats can be assessed. Site-specific FRV of peatlands in Ireland are measured using two parameters (Fernandez et al., 2014): 1) the current versus target area of Annex I habitat type ‘active raised bog’ (ARB; code 7110), and 2) the quality of ARB, measured by the proportion of central ecotope and active flush/soaks (i.e. more pristine examples of ARB vegetation complexes; Table 5.2) of the total current area of ARB. The status of a peatland is then assessed based on current FRV and changes in FRV over multiple survey periods. The label for current FRV falls into either Favourable (greater, equal, or 0–5% below target area), Unfavourable Inadequate (5–15% below target area), or Unfavourable Bad (>15% below target area), while the trend value is assessed as Stable, Improving, or Declining depending on the change in extent of central ecotope and active flush/soaks within ARB (Table 5.1). In our study, we selected the five peatlands based on the FRV of current versus target area of ARB, ranging from relatively intact (FRV of -14% in Carrowbehy) to relatively degraded (FRV of -67% in Moyclare) with a minimum requirement that all peatlands still contained central ecotope. All studied peatlands are currently part of Irelands’ Special Areas of Conservation (SAC’s) network under the EU Habitats Directive (92/43/EEC). While intermittent hydrological restoration with drain blocking dates back as far as 1984 on Mongan, all sites have been subject to much restoration work between 2016–2022 through the Living Bog LIFE restoration project (LIFE14 NAT/IE/000032).

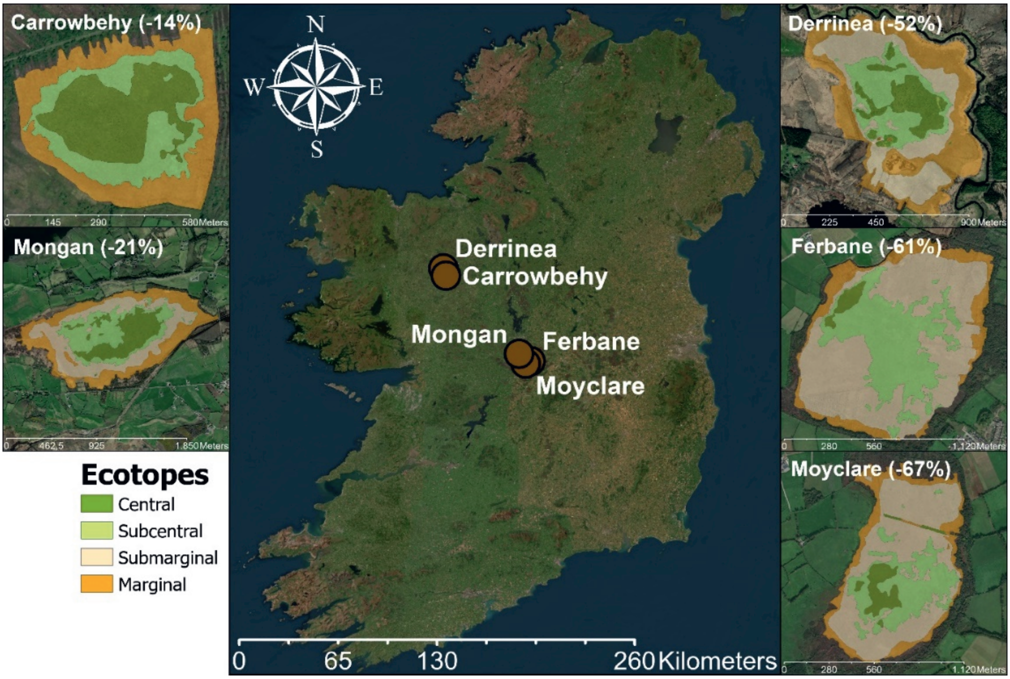


Figure 5.1 Study area maps showing the five Irish peatlands mapped in this study. Original polygon-shaped field-based ecotope maps from the Irish National Parks and Wildlife Service (NPWS) are displayed on top of the base imagery. All peatlands in this study are currently part of Irelands' Special Areas of Conservation (SAC) network under the EU Habitats Directive (92/43/EEC). Peatlands in this study area map are sorted and presented from top left to bottom right in order from most intact to most degraded according to their Favourable Reference Values. The percentage behind each peatland name represents the FRV value of current versus target area of Annex I habitat type 'active raised bog' (7110; Fernandez et al., 2014). The ecotope map from Carrowbehy used in this study was developed in 2017, while the ecotope maps for Derrinea, Mongan, Ferbane, and Moyclare were developed in 2023, 2022, 2021 and 2020 respectively.

Table 5.1 Overview of characteristics of the studied peatlands. Represented per peatland are its name, peatland type, extent, area of active raised bog (ARB), favourable reference value (FRV) of the current versus target area of ARB, current status, past impact, and timeline of recent restoration efforts. Peatlands are sorted from top to bottom by order of decreasing favourable reference value.

Peatland	**Type**	**Extent**	**ARB**	**FRV**	**Current status**	**Past impact**	**Restoration timeline**
Carrowbehy	Western raised bog	35ha	61.1%	-14%	Unfavourable Inadequate-Declining	Peat cutting Drainage Forestry	November 2019–March 2020
Mongan	Midland raised bog	205ha	39.6%	-21%	Unfavourable Bad-Improving	Peat cutting Drainage	September 2018–December 2021
Derrinea	Western raised bog	86ha	30.3%	-52%	Unfavourable Bad-Declining	Peat cutting Drainage	January 2017–December 2022
Ferbane	Midland raised bog	153ha	32.4%	-61%	Unfavourable Bad-Declining	Peat cutting Drainage	August 2019–December 2019
Moyclare	Midland raised bog	130ha	31.4%	-67%	Unfavourable Bad-Declining	Peat cutting Drainage	December 2018–August 2019

5.2.2 Field-based habitat mapping approach

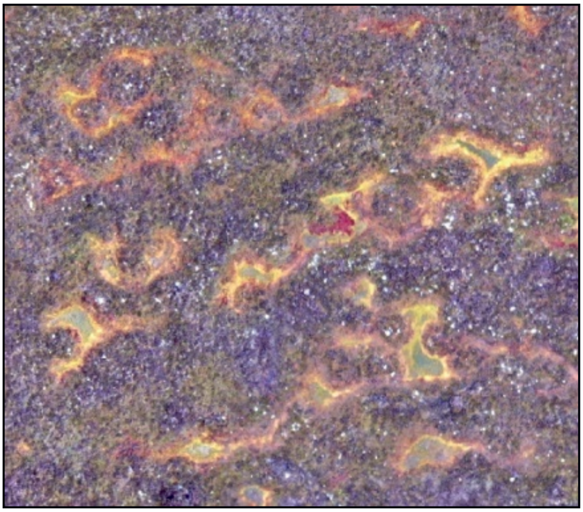
The Irish ecotope mapping approach has been developed and used to report on the conservation status of Habitats Directive Annex I habitats, particularly of Active Raised Bog (ARB; code 7110) with field-based surveys carried out for a large proportion of designated raised bogs in Ireland every 6 years since the development of the ecotope framework by (Kelly, 1993). This framework involves grouping and mapping several ecotopes based on homogeneous mosaics of distinct vegetation complexes and a typical associated depth of acrotelm and hydrological and hydro-chemical characteristics (Table 5.2; see Fernandez et al., 2014; Kelly, 1993; Schouten & Kelly, 2002 for further details). The ecotope classification system is based on an idealised concentric vegetation zonation from the centre of a raised bog to the margin. However, as a result of subsidence, this concentric pattern of ecotopes no longer occurs across many sites. Nonetheless, the characteristics of each ecotope can remain, but now exist in a more eccentric pattern across a bog. The main concentric-type ecotopes range from central (typically the wettest and indicative of excellent quality ARB) through to subcentral, submarginal, marginal, and facebank, which is the driest ecotope type generally occurring at the edges of peatlands because of turf cutting or drainage. Actively accumulating peat conditions occur only within the central and subcentral ecotopes (Table 5.2). Outside of the concentric system, two additional ecotopes exist that are called flushes and soaks. These can be either active (i.e. ARB) or inactive. Repeated ecotope mapping over time has allowed even small changes in habitat quality to be measured.

During a field survey, the entire bog is walked using sub-metre GPS equipment, but particular attention is given to: 1) areas of the bog that were identified as potentially having changed due to impacts, 2) ecotope boundaries and particularly the boundary between subcentral and submarginal ecotope as this is defined as the boundary of ARB, and 3) areas of the bog modelled as potentially supporting ARB (see National Parks and Wildlife Service, 2018for further details on the model). In our study we used the most recently developed habitat maps for each peatland as a ground-reference map for development of a ground-reference dataset used in classification (see also 2.3.3). Dates of maps ranged from 2017 (Carrowbehy), 2020 (Moyclare), 2021 (Ferbane), and 2022 (Mongan), to 2023 (Derrinea). While the least up-to-date habitat map for Carrowbehy was produced five years prior to drone imagery acquisition, we argue this timeframe is too short for impactful changes to have happened to microform and plant functional type patterns in this peatland.

Table 5.2: Overview of the general abiotic and biotic characteristics of peatland habitats in the five studied Irish peatlands.

Habitat characteristics

Central – Active raised bog (ARB)



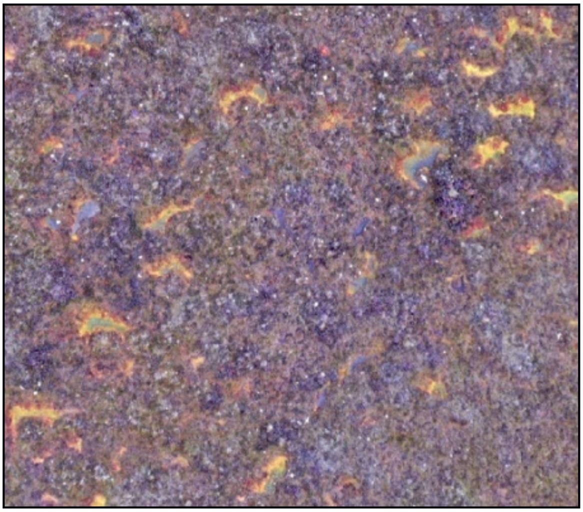
Soft, often quaking surface. Often well-developed microtopography ranging from open water pools to high hummocks. Pools do not have to be present for an area to be classified as central.

Hollow: Frequent. Often *Sphagnum cuspidatum* dominated in midland sites.

Lawn: Frequent. Sphagnum papillosum and Sphagnum medium dominated.

Hummock: Frequent. Sparce cover of *Calluna vulgaris* and *Eriophorum vaginatum*.

Subcentral – Active raised bog (ARB)



Surface usually soft, sometimes hard. Moderately developed microtopography ranging from hollows to hummocks. Generally, lawn dominated with a few hummocks.

Hollow: Present. Signs of desiccation. Reduced *Sphagnum cuspidatum* cover, increased algal cover.

Lawn: Frequent. Can be *Sphagnum papillosum* and *Sphagnum medium* dominated or covered with *Rhynchospora alba, Narthecium ossifragum* or on western sites (Carrowbehy, Derrinea) can be *Carex panicea*

Hummock: Frequent. Moderate cover of *Calluna vulgaris* and *Eriophorum vaginatum*.

Table continues on the next page

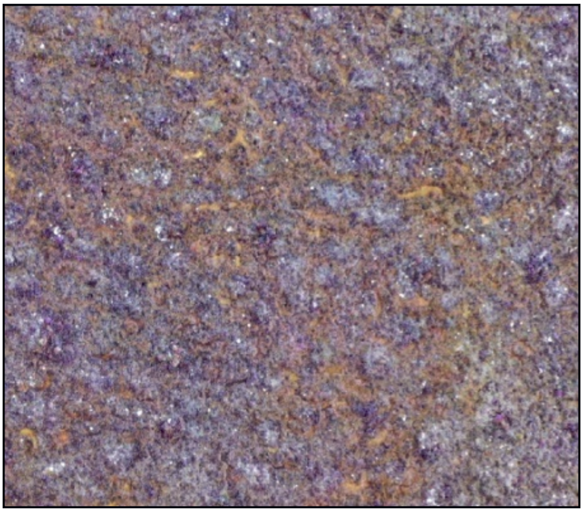
Submarginal – Inactive raised bog (IRB)

No quaking surface. Wetter vegetation types absent except for *Narthecium ossifragum* dominated lawns.

Hollow: Sparse. Pools absent.

Lawn: Frequent. Increase in *Narthecium ossifragum* cover relative to subcentral and a corresponding decrease in cover of *Sphagnum*.

Hummock: Frequent. Increase in *Calluna vulgaris* and *Eriophorum vaginatum* relative to subcentral.



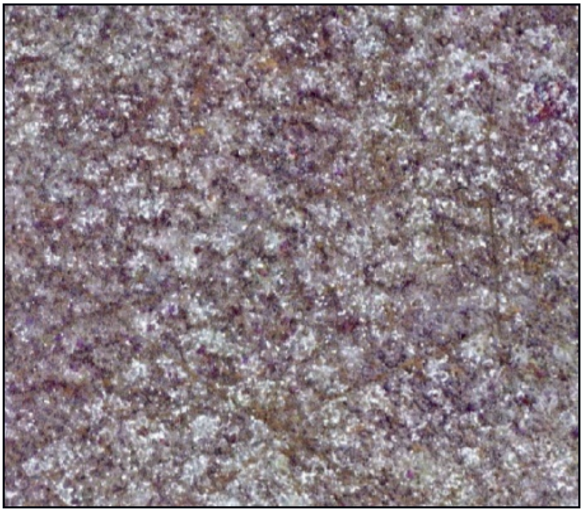
Marginal – Inactive raised bog (IRB)

Hard surface. Low water level. Poorly developed microtopography. Pools absent.

Hollow: Absent.

Lawn: Present/frequent. *Narthecium ossifragum*, *Trichophorum cespitosum* or on western sides (Carrowbehy, Derrinea) can be *Carex panicea* dominated.

Hummock: Common. *Calluna vulgaris* dominated, *Cladonia portentosa* sometimes abundant.



5.2.3 Drone-based vegetation mapping approach

5.2.3.1 Drone imagery acquisition and field survey

Drone imagery of each peatland was captured using a DJI Mavic 2 Pro with Hasselblad L1D-20c red-green-blue (RGB) camera sensor between 6 and 12 September 2022. We used automated flight mode at 120m altitude with 75/60 forward/side overlap with default camera calibration in the EXIF information with focal length of 10.3mm. Flight lines extended well beyond the edges of each peatland to increase the number of overlapping images at the peatland margins for use during photogrammetry. We conducted each flight within one hour of solar noon and on largely overcast days with wind speeds <28km/hr. Exception to the latter was Derrinea. Here the flights occurred on a day with scattered cumulus clouds, leading to partial shading and overexposure of the surveyed area. We collected drone imagery of parts of each peatland at 40m flight altitude to use as reference datasets to validate the allocation of ground-reference samples used in the classification of each fine-scale vegetation class (see also 2.3.3). Lastly, we extensively visited most areas of each peatland to establish the most dominant plant functional types within the study area. For more details on image acquisition in this study, see (Steenvoorden & Limpens, 2023).

5.2.3.2 Pre-processing drone imagery products and deriving predictor variables

After all drone imagery was acquired, we used ortho-mapping software in ArcGIS Pro to produce a stitched RGB colour orthomosaic with a spatial resolution of 2.7cm. Besides, we created a Digital Terrain Model (DTM) of each peatland with a spatial resolution of 13.5cm using extended terrain matching, which is a feature-based stereo-matching technique for generating high-density point clouds. We georeferenced the drone-derived imagery products of all peatlands within ArcGIS Pro, where we matched imagery products with the underlying Worldview-2 imagery basemap using 10 ground control points (4 at each corner, and 6 within the peatland) and clearly defined tie-points in both datasets. Hereafter, we transformed each orthomosaic and DTM for each peatland using a spline function. While this led high visual accuracy and root mean squared errors of near zero, it was hard to evaluate georeferencing accuracy over the whole peatland. To extract fine-scale variations in microtopography within each peatland and remove the convex shape of the DTM from centre to margin, we detrended each DTM using moving-window averaging with a window of 10-by-10m to better reflect the slight dome shape of the peatlands. We chose this moving-window size because a sensitivity analysis on moving-window sizes up until 128m showed that using moving-window sizes below 10m reduced classification performance, and the 10m window matches with the general size of microforms. To enhance the efficiency of the classification process, we resampled both the orthomosaic and detrended DTM to 0.25m spatial resolution for each peatland using bilinear resampling (Steenvoorden & Limpens, 2023), which determines the new value of a cell based on a weighted distance average of the four nearest input cell centres.

After creating and georeferencing the orthomosaics and DTMs for all peatlands, we used each RGB orthomosaic to calculate the Hue-Saturation-Value (HSV) colour model values and ten other vegetation colour indices for each pixel (variables combining two or more RGB bands; see Table S5.1). We used HSV colour model values and RGB colour indices in this study because they are better suited for emphasising spectral differences between fine-scale vegetation classes than individual RGB reflectance values (Steenvoorden et al., 2022). Hereafter, we converted all pixels in the newly created orthomosaic into segments (objects) using the Quickshift and SLIC image segmentation algorithms in Python’s Scikit-image module for microforms and plant functional types respectively (Achanta et al., 2012; Van Der Walt et al., 2014). Quickshift is a relatively recent image segmentation algorithm that groups similar pixels into segments by iteratively comparing their colour and spatial proximity to seed points (Vedaldi & Soatto, 2008), forming segments or regions in an image. We used Quickshift for microforms because it can create more variably sized segments depending on spectral homogeneity, and used SLIC for plant functional type classifications because it can set minimum segment sizes for an image and creates more rectangular segments. This allowed us to segment individual plants more accurately and easily than the Quickshift algorithm.

After separately segmenting the orthomosaic for both microforms and plant functional type classifications, we computed the mean values of each newly created spectral predictor variable for all segments by averaging the values of all pixels that were fully contained by each unique segment. We also calculated eight spatial patch metrics for each unique segment using Python’s SimpleITK package (Yaniv et al., 2018). In total, this resulted in the development of 25 predictor variables for the classification of microforms and plant functional types, among which the mean reflectance values of the individual RGB bands, mean of HSV colour model values, ten vegetation colour indices, eight spatial patch metrics, and mean value of the detrended DTM which corresponds to the topographic position index with 10m neighbourhood (Table S5.1). We chose to compute only the mean value of the detrended DTM because we argue this is the most direct topographic driver of microform and plant functional type distribution, at least in our study area. We computed normalized ratios for each band to account for their intensity in relation to the two other bands, which is more indicative of their actual colour than using only one band. Furthermore, we computed seven other vegetation indices using two or more RGB bands to emphasise spectral differences among our vegetation classes compared to solely RGB reflectance. For instance, the excess greenness index we computed in our study tends to outperform many other indices in discriminating between vegetation types (Larrinaga & Brotons, 2019). We also computed eight commonly used spatial patch metrics to evaluate whether the spatial characteristics of resulting segments were indicative of specific microforms and their associated plant functional types. Lastly, we performed a sensitivity analysis for both segmentation algorithms where we systematically classified both microforms and plant functional types using multiple combinations of their parameters. Afterwards, we evaluated the effect of each parameter combination in Scikit-image on both classification performance and visual accuracy of each resulting segmented raster. Hereafter we decided on the most “optimal” parameterisation for this study by selecting among all developed models within 2% of the highest performing model but with the largest segment size possible to optimise computational efficiency. For SLIC, this resulted in using the default parameters where we only set minimum segment size to 0.5m for microform classifications and to 0.25m for plant functional type classifications (Steenvoorden & Limpens, 2023).For Quickshift we kept most parameters at default but adapted max_dist to 5, kernel_size to 1, and sigma to 0.7 for both microform and plant functional type classifications.

5.2.3.3 Development of ground-reference datasets

5.2.3.3.1 Fine-scale vegetation classes and sampling strategy

We divided fine-scale vegetation patterns into microforms and plant functional types, which are two common conceptualizations used in mapping vegetation and functions in peatlands. Microforms were subdivided into three classes, representing the relative position of the surface above the water table: 1) hollow, 2) lawn, and 3) hummock (Table S5.2). While hollows could technically be subdivided further into open water pools with no considerable amount of vegetation, we decided to treat open water and hollow as one class in our study due to their largely overlapping characteristics and functions. Plant functional types comprised five classes: 1) peat moss, 2) shrub, 3) graminoid, 4) lichen, 5) open water (Table S5.2) and 6) trees. We chose the first four vegetation classes because they are the most dominant functional types within our studied peatlands, and best represent above-canopy vegetation as seen from our drone imagery. Trees were included as a sixth plant functional type in Ferbane and Moyclare because they had notable cover at the peatland margins and could potentially be helpful in distinguishing between central and marginal ecotopes because it is an indicator of surface drying.

For the classification of microforms in each peatland, we adopted a combined random and targeted sampling strategy to a create ground-reference dataset with training/testing samples. For microforms we initially placed and labelled 400 (80% of total) randomly placed points throughout each peatland. If these preliminary 400 ground-reference samples did not result in severe underrepresentation of one of the microform classes, we added and labelled another 100 randomly placed points throughout that peatland for a total ground-reference dataset of 500 samples. However, if the preliminary 400 ground-reference samples were severely skewed towards hummock and lawn, we manually added and labelled several hollow points in combination with randomly allocating the rest of the ground-reference points to a total of 500. In the end, we only manually added some hollow ground-reference samples for Ferbane, Mongan, and Moyclare. Because relative proportions of microforms differed among peatlands, the final allocation of ground-reference samples for microforms differed per peatland (Table S5.3). In contrast to microforms, we adopted a fully targeted sampling approach for ground-referencing of plant functional type classifications. Here, we manually placed 100 points per plant functional type within each orthomosaic to prevent underrepresentation of uncommon plant functional types within each peatland. To ensure that plant functional types were proportionally sampled across the whole orthomosaic, we created a 10x10 fishnet grid over each orthomosaic and took one sample per plant functional type from each of the 100 sub-grids. If a sub-grid did not contain a sample for a specific vegetation class, we took two from the next one and so forth. We also aimed to ensure representativeness of variation within each plant functional types by selecting a variation of more and less dense patches of vegetation for that class. We argue a total sample size of 500 is adequate for mapping of both fine-scale vegetation patterns because a sensitivity analysis on ground-reference dataset size in a previous study showed that consistent vegetation classifications were made for highly similar Irish peatlands even with only 250 ground-reference samples (Steenvoorden et al., 2023).

5.2.3.3.2 Peatland habitats and sampling strategy

In this study, we subdivided our large-scale mapping units into both ecotopes and peat accumulation status (hereafter: status) in accordance with (Fernandez et al., 2014). Here, ecotopes are a classification framework for habitat distribution, while status is more directly indicative of habitat quality and ecosystem functioning by separating areas with active peat accumulation from those that are not actively accumulating peat. We distinguished and subdivided ecotopes into four classes during mapping: 1) central, 2) subcentral, 3) submarginal, and 4) marginal (Table 5.2; see also 2.2). While the field-based mapping approach of (Fernandez et al., 2012) considered facebank as an additional independent fifth ecotope, we decided to merge facebank with the marginal ecotope in this study because of largely overlapping spatial, structural, and functional characteristics. The NPWS also separately categorizes existing active and inactive flushes, but we merged these ecotopes with central and marginal ecotopes respectively because these occurred only in very small proportions in Derrinea and Moyclare and shared similar spectral and functional characteristics. For status classifications we considered the classes active raised bog (ARB) and inactive raised bogs (IRB) by grouping the central and subcentral ecotopes as ARB and grouping the submarginal and marginal ecotopes as IRB (Table 5.2).

To create the ground-reference dataset for mapping ecotopes and status, we first converted the outline of the original field-based and polygon-shaped NPWS ecotope map of each studied peatland to a fishnet grid polygon feature with rectangular cell sizes of 20x20m that covered the whole outline (Figure 5.2). We decided to use this grid size because it corresponds to the minimum mapping size that the NPWS uses for delineating ecotopes in the field (Fernandez et al., 2014). We then removed all 20x20m grids at the edges of each peatland that were not completely situated within an NPWS ecotope map. Because the studied area of the peatlands ranged strongly in size between 35–124ha, the total number of 20x20m grid cells within each peatland also varied between 657 for Carrowbehy to 2911 for Mongan. Afterwards, we labelled each 20x20m grid cell by overlaying it with the original polygon based NPWS ecotope map and assigning the ecotope and status label to the class with the highest combined area within each 20x20m grid cell.

5.2.4 Vegetation classifications

5.2.4.1 Microforms and plant functional types

We classified microforms and plant functional types using the ensemble classifier Random Forest (RF; Breiman, 2001) in Python's Scikit-learn module (Pedregosa et al., 2011) where we created two separate RF models per peatland: one for microforms and one for plant functional types. Within each RF model, we employed all 25 predictor variables (Table S5.2) as input datasets and selected all segments that fell within each point of the previously developed ground-reference dataset for that peatland and vegetation pattern as training/testing samples. We used the default parameters for RF classifiers in Scikit-learn: n_estimators (trees) of 100, max_depth = None, min_samples_split = 2, min_samples_leaf = 1, and max_features = 'sqrt'. Hereafter, we split all samples in the ground-reference dataset using five-fold stratified cross-validation with an equally sized separate validation set (in this study: the set of ground-reference samples that a model has never seen in training/testing). This is analogous to a ratio of 66.6/16.7/16.7 for training/testing/validating. After fitting each RF model using the training/testing dataset, classification performance per vegetation class as well as final classification performance was computed by averaging precision, recall, and F1-score over all folds using both the testing and validation samples. The F1-score (0–100%) measures the harmonic mean of precision and recall for each vegetation class, therefore providing a more nuanced evaluation of classification performance over all vegetation classes which was crucial as we aimed to optimise mapping accuracy for all vegetation classes. We also compared differences in classification performance between the testing and validation samples to evaluate model overfitting on the training data. Ultimately, we classified all segments within each orthomosaic for each vegetation pattern separately by taking the most frequently predicted vegetation class for each segment over all five folds, resulting in a final map of microforms and plant functional types for each peatland. Lastly, we retrieved an overall ranking of variable importance for each final RF model by computing the Gini importance for each fold and averaging it over all folds to retrieve stable mean importance values for each final model (Behnamian et al., 2017).

5.2.4.2 Ecotopes and peat accumulation status

After we completed classifications of both microforms and plant functional types, we computed the proportions of all vegetation classes, as well as computed the range (max-min) in detrended DTM values for each 20x20m grid cell per peatland. This resulted in nine (or ten in Ferbane and Moyclare) predictor variables for classifications of ecotopes and peat accumulation status. Subsequently, we classified ecotopes and status using a Support Vector Classifier (SVC) with linear kernel and a regularization parameter (C) of 1 (default parameters) in Python's Scikit-learn module (Pedregosa et al., 2011), utilizing all labelled 20x20m grid cells from the ground-reference dataset as input data. We chose to use a linear SVC for classification of ecotopes and status instead of Random Forest (RF) because the relationship between the proportions of microforms and plant functional types and their corresponding ecotope or status is deemed linear in theory (see also 2.2). Besides, we standardised all predictor variables using z-scores because SVC are sensitive to the scale of input predictor variables. Standardisation therefore ensured that all predictor variables had the same scale, which simultaneously also facilitated standardised interpretation of the model coefficients (variable importances).

Within the SVC classification approach, we also split all ground-reference samples using five-fold stratified cross-validation with a validation set, analogous to a ratio of 66.6/16.67/16.7 for training/testing/validating. We included a validation set of 16.7% of the total ground-reference dataset here because the ground-reference dataset for classification of ecotopes and status covers the whole peatland. Consequently, the validation set could be used to ensure that the SVC models are not overfitting on the training data of each model because of the relatively large training sample size with respect to the size of the whole peatland. After fitting each SVC model for ecotopes and status, we assessed classification performance per vegetation class and the final classification performance by averaging precision, recall, and F1-score over all folds using both the testing and validation samples. We also evaluated classification performance of the SVC models when separately only using the proportions of microforms or the plant functional types as input predictor variables, as well as using a model without the range in detrended DTM. In the end, we used each peatland-specific SVC model to classify the ecotope and status for every 20x20m grid cell in the ground-reference dataset. We also computed the variable importance for each SVC model by averaging the coefficients of each input predictor variable over all folds. Lastly, we converted all 20x20m grid cells for each peatland into a point feature using their centroid and calculated the average distance of each centroid point to a habitat margin. We then performed a Wilcoxon rank-sum test between the correctly classified and misclassified 20x20m grid cells to evaluate whether misclassifications occurred disproportionally more at the habitat margins. We performed Wilcoxon rank-sum tests here because the distances between centroid points and a habitat margin were notably right-skewed.

5.2.5 Spatial transferability analysis

To test to what extent habitat classification models were transferable between the studied peatlands, we compared the ecotope and status maps from each peatland-specific support vector classifier model (SVC) to the ecotope and status maps from a pooled SVC model using cluster sampling with five folds. This meant that in each of the five folds, we trained an SVC model on four of the studied peatlands while predicting on the fifth peatland until all peatlands were classified. To create the final pooled ground-reference dataset for each fold, we first grouped all ground-reference samples from the four ‘training’ peatlands into a raw pooled ground-reference dataset. Hereafter, we created a stratified subset from the raw pooled ground-reference dataset with the same size and distribution as the fifth ‘prediction’ peatland to be used as the final pooled ground-reference datasets. For instance, because the peatland-specific ground-reference dataset of Carrowbehy had 647 ground-reference samples, we also took a stratified subset of 647 samples from the raw pooled ground-reference dataset. Here, we used the proportions of ecotopes and status from the peatland-specific ground-reference dataset to retrieve a stratified estimation of ground-reference samples for the final pooled ground-reference dataset. This cluster sampling approach ensured that each final pooled ground-reference dataset used for training contained no ground-reference samples from the peatland to be classified. Besides, using an equal number of ground-reference samples for each vegetation class in both peatland-specific and pooled ground-reference datasets facilitated a standardised comparison of classification performance between both the peatland-specific and pooled approach. For example, because Carrowbehy did not contain a submarginal ecotope, inclusion of submarginal ground-reference samples within the newly created stratified subset ground-reference dataset from the full pooled ground-reference dataset would be obsolete. In some cases, the total number of ground-reference samples for a specific ecotope class was lower in the pooled ground-reference dataset than in the peatland-specific ground-reference dataset. When this happened, we used the maximum number of samples for that specific ecotope from the pooled ground-reference dataset and redistributed the remaining samples proportionally over the other ecotopes. A full workflow of the methodology used in this study can be seen in Figure 5.2.

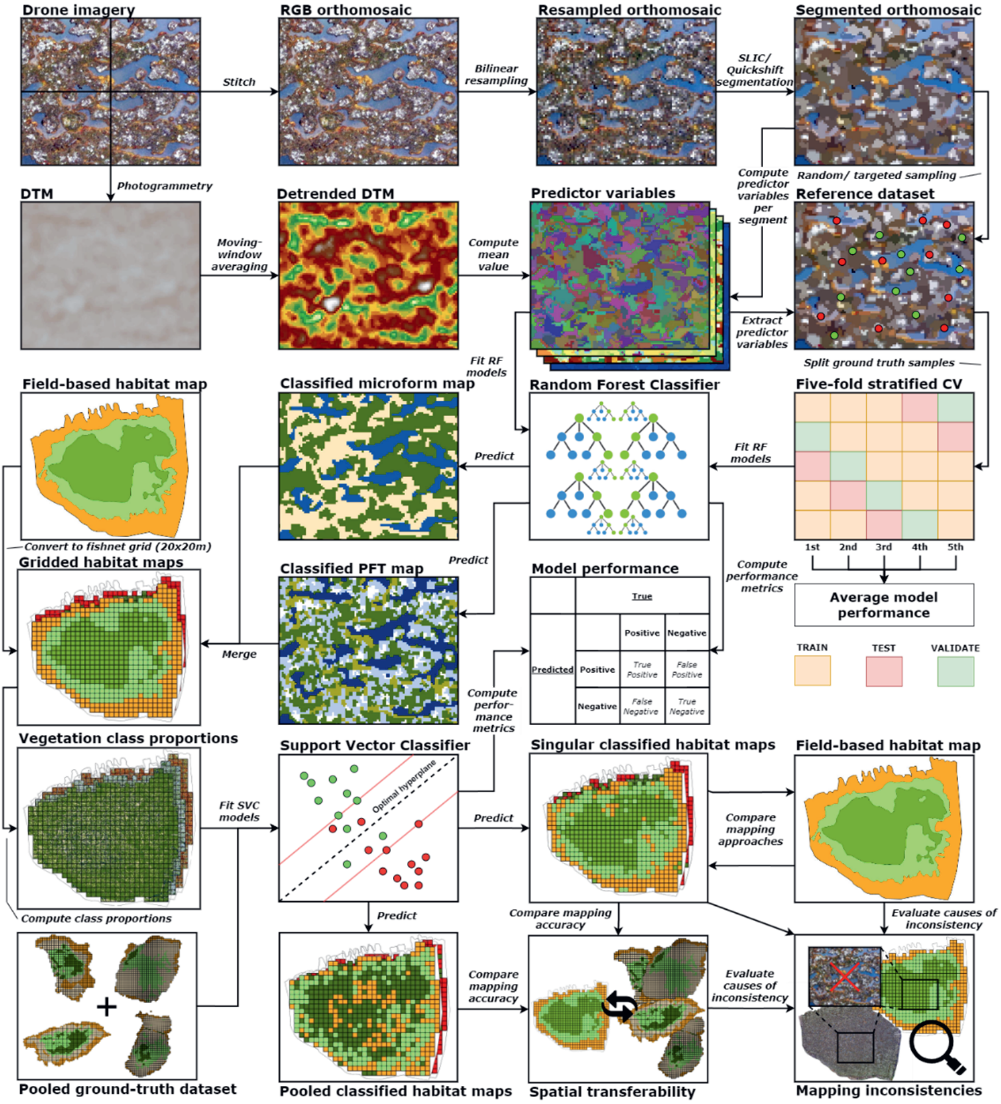


Figure 5.2 Schematic and visual representation of the workflow used in this study to classify fine-scale vegetation patterns (microforms and plant functional types [PFT]), ecotopes (habitat distribution) and status (habitat quality) in five Irish peatlands ranging in size from 35–124ha. Visualized are the processes and raster/polygon datasets used to go from initial drone imagery to final habitat maps. Image snippets for the pre-processing of drone imagery, as well as the outline of the field-based habitat map are based of Carrowbehy. The field-based habitat map was created by the Irish National Parks and Wildlife Service (NPWS).

5.3 Results

5.3.1 Microform and plant functional type classifications

Classifications of both microforms and plant functional types showed consistently high model performances, with overall F1-scores of 96% and 93% respectively for all peatlands (Table 5.3). Besides, classification performance between the validation and testing set was always near equal for each peatland (Figure S5.1), which highlights that that none of the Random Forest (RF) models were overfitting on the training data. Classification performance was highest for microforms in Carrowbehy and Moyclare (96%), and lowest for plant functional types in Derrinea (90%). Classification performance for specific vegetation classes did vary per bog. For instance, while classification of hollows was generally high in Carrowbehy (96%), Moyclare (96%), and Mongan (95%), it was lower in Derrinea (90%) and Ferbane (87%), even though Derrinea contains relatively large and distinguishable pools and aquatic peat moss carpets. Misclassifications for microforms occurred most often between lawns and hummocks (Table S5.4), but also sometimes between hollow and hummock (Table S5.4). While average classification performance for plant functional types was consistently high (93%) and most individual plant functional types were also classified consistently well in most peatlands (F1-scores >90%), classification performance was always lowest for graminoids (86% on average over all peatlands; Table 5.3). Most misclassifications for plant functional types occurred between peat moss and graminoid, shrub and graminoid, graminoid and lichen, graminoid and trees, and open water with shrub (Table S5.5; discussion section 5.4.2).

Analysis of variable importance emphasised that a combination of several different colour vegetation indices, mean value of the detrended DTM, hue, and saturation were often in the top five most important predictor variables for distinguishing between microforms, while value (HSV) and individual RGB bands were often of less or no importance at all (Figure S5.3–S5.7). In contrast with microforms, individual RGB bands were often in the top five most important predictor variables during the classification of plant functional types in combination with mean value of the detrended DTM and mean hue, saturation, and value (Figure S5.8–S5.12).

Table 5.3 Overview of averaged classification performances (F1-score; 0–100%) over all five folds for Random Forest (RF) models used in classification of microforms and plant functional types in the five Irish peatlands used in this study. Represented are each of the five studied peatlands sorted from left to right in order from most intact (Carrowbehy) to most degraded (Moyclare), as well as class-specific and overall F1-score for both vegetation patterns within each peatland and averaged overall classification performance for each vegetation pattern over all peatlands.

Peatlands	**Carrowbehy**	**Mongan**	**Derrinea**	**Ferbane**	**Moyclare**
Microform	**Average F1-score (0–100%)**				
Hollow	96.2	95.1	90.4	87.1	96.2
Lawn	95.6	93.5	92.8	94.0	95.6
Hummock	96.8	96.5	96.0	96.6	96.8
Overall	96.4	95.4	94.0	95.4	96.4
Average	***Average overall F1-score for Microform: 95.5%***				
Plant functional type	**Average F1-score (0–100%)**				
Peat moss	92.8	99.7	95.8	95.3	95.2
Shrub	91.8	95.9	88.9	90.8	94.7
Graminoid	87.4	86.8	79.5	88.0	85.9
Lichen	97.0	88.5	91.0	96.5	93.2
Open water	96.4	97.4	92.9	98.3	98.3
Tree	n/a	n/a	n/a	90.2	95.7
Overall	93.0	93.6	89.7	93.2	93.8
Average	***Average overall F1-score for PFT: 92.7%***				

5.3.2 Ecotope and status classifications

5.3.2.1 Classification performance

Average classification performance for status using all predictor variables was notably higher than those of ecotopes, aligning for 88% and 72% respectively (F1-scores) with the conventional maps. For both ecotopes and status, classification performance between the test and validation datasets were near equal (Figure S5.2), which implied that the Support Vector Classifier (SVC) models were not overfitting on the training data during classification in any of the peatlands. Average classification performance for ecotopes differed between peatlands as well, ranging from 80% in Carrowbehy to 67% in Derrinea (Figure 5.4; Table S5.11). Classification performance for status was consistently higher although equally variable, ranging here from 92% in Mongan to 79% for Ferbane. Classification performance also differed notably among specific ecotopes for individual peatlands. For example, classification performance for central ecotopes was 87% for Carrowbehy, but only 79% for Mongan, 77% for Ferbane, 70% for Derrinea, and even only 31% for Moyclare (Table S5.11). Moreover, classification of marginal ecotopes were sometimes very low, aligning only by 47% and 21% (F1-scores) for Ferbane and Moyclare, meaning that over half of all 20x20m grid cells in these peatlands that were labelled as marginal were classified as a different ecotope. The confusion matrices for ecotope classifications show that misclassifications most often occurred between adjacent ecotopes (from central to subcentral, to submarginal to marginal; Table S6; Figure 5.3D; Figure S5.28–S5.32). The results from our Wilcoxon rank-sum tests also support this by highlighting that misclassifications of ecotopes and status occur disproportionally closer to the boundary of a peatland habitat than correct classifications (Table S5.10).

5.3.2.2 Variable importance

When ecotope classifications were carried out with only microforms or plant functional types as input predictor variables, average classification performances dropped by 9% (to 63%) and 5% (to 67%) respectively over all peatlands. In contrast, the inclusion of the range in detrended DTM values was only marginally impactful and increased average classification performance by only 1%. Analysis of variable importance for classifications of ecotopes through the resulting coefficients from the SVC models highlight that the role of specific microforms and plant functional types were relatively comparable over all peatlands (Figure

S5.13–S5.17), especially when peatlands shared similar vegetation characteristics throughout the landscape. While peat moss was in the top three most important predictor variables in Mongan and Moyclare, it was not included for Carrowbehy, Derrinea, and Ferbane. Overall, the proportion of hollow and open water were in the top three most important predictor variables for all peatlands, likely for their strong direct relationship with surface wetness. Interestingly, lichen and tree cover were also in the top three most important predictor variables in the classification of ecotopes for Ferbane and Moyclare (the only two peatlands in which trees were mapped; Figure S5.16–S5.17), likely because lichen and trees mostly occurred around the peatland margins. Open water was also a relatively valuable predictor variable in Ferbane, even though Ferbane does not contain any natural open water pools in the peatland centre. Here, the artificially created pools resulting from infilled drainage ditches occurred only at the peatland margin, and likely played a role in improving the classification of submarginal ecotopes for this peatland. In contrast to ecotope classifications, classifications of status were less impacted when microforms and plant functional types were used separately as predictor variables, and average classification performances dropped only by 7% (to 81%) and 3% (to 85%) over all peatlands. Furthermore, inclusion of the range in detrended DTM values was even less important in models for status, increasing average classification performance by only 0.3%. Relative variable importance for classification of status differed from that of ecotopes (Figure S5.18–S5.22), but the proportion of peat moss and hollow were still mostly in the top three predictor variables for all peatlands, including the proportion of lawn. In Ferbane, proportion of trees was the second most important predictor variable for distinguishing between ARB and IRB.

5.3.3 Spatial transferability analysis

Classification performance for ecotopes dropped notably for each peatland when using a pooled ground-reference dataset versus using a peatland-specific (singular) ground-reference dataset (Figure 5.4). Misclassifications for each peatland increased mostly because classified maps using a pooled ground-reference dataset led to more eccentric (pixelated) maps (Figure 5.3; Figure S5.28–S5.32). This contrasts with the peatland-specific maps, which were relatively concentric (circularly zoned) because they used the habitat maps from the National Parks and Wildlife service as ground-reference dataset. Particularly, using the pooled ground-reference dataset reduced overall alignment from 72% to 62% (-10%) versus the models using a peatland-specific (singular) ground-reference dataset (Table S11). We observed that reductions in classification performance for ecotopes were less notable in Ferbane and Moyclare which are some of the more degraded peatland sites in our study (Figure 5.4). Classifications of status were less sensitive when using pooled ground-reference datasets than those of ecotopes (Figure 5.4; Table S5.11), as average overall classification performance dropped only by 5% from 88% to 83%. Reductions in classification performance of status for individual peatlands showed similar patterns as those for ecotopes, with largest drops in classification performance for Carrowbehy (-10%), Derrinea (-7%), and Moyclare (-5%), whereas model reductions were small for Ferbane (-3%) and Mongan (-1%; Figure 5.4; Table S5.11). Looking closer, we found that proportions of microforms and plant functional types associated with the classes of both ecotopes and status of the National Parks and Wildlife Service maps varied between peatlands (Figure 5.5; Figure S5.33–S5.34). This effect generally led to overrepresentation of central and subcentral ecotopes and active raised bog in Carrowbehy, Derrinea, and Mongan (more intact peatlands; Table 5.1; Figure S5.28–S5.32), while resulting in underrepresentation of the same classes in Ferbane and Moyclare (more degraded peatlands; Table 5.1; Figure S5.28–S5.32). Besides, the effect of the lack of uniformity in vegetation proportions on spatial transferability was more pronounced for ecotopes than status maps (Figure 5.3; Figure S5.28–S5.32), potentially explaining their poor transferability.

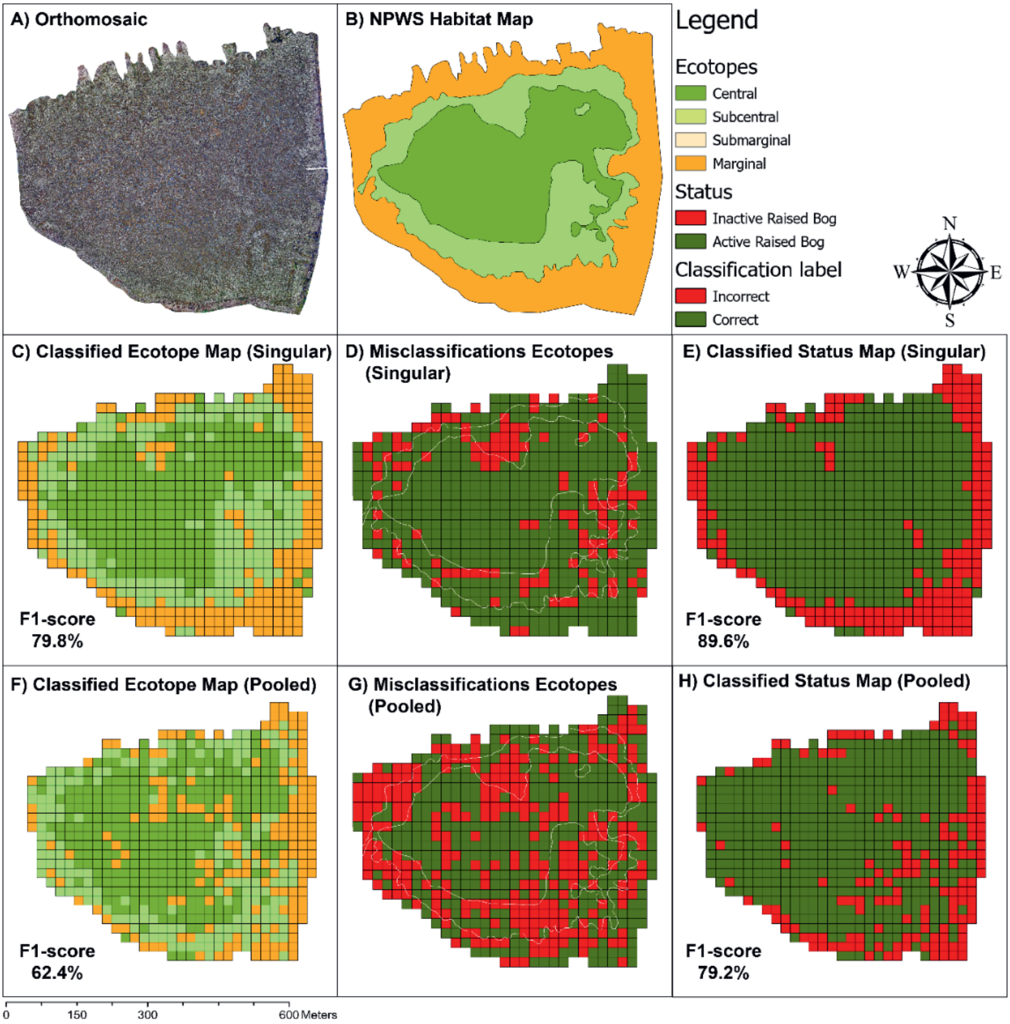
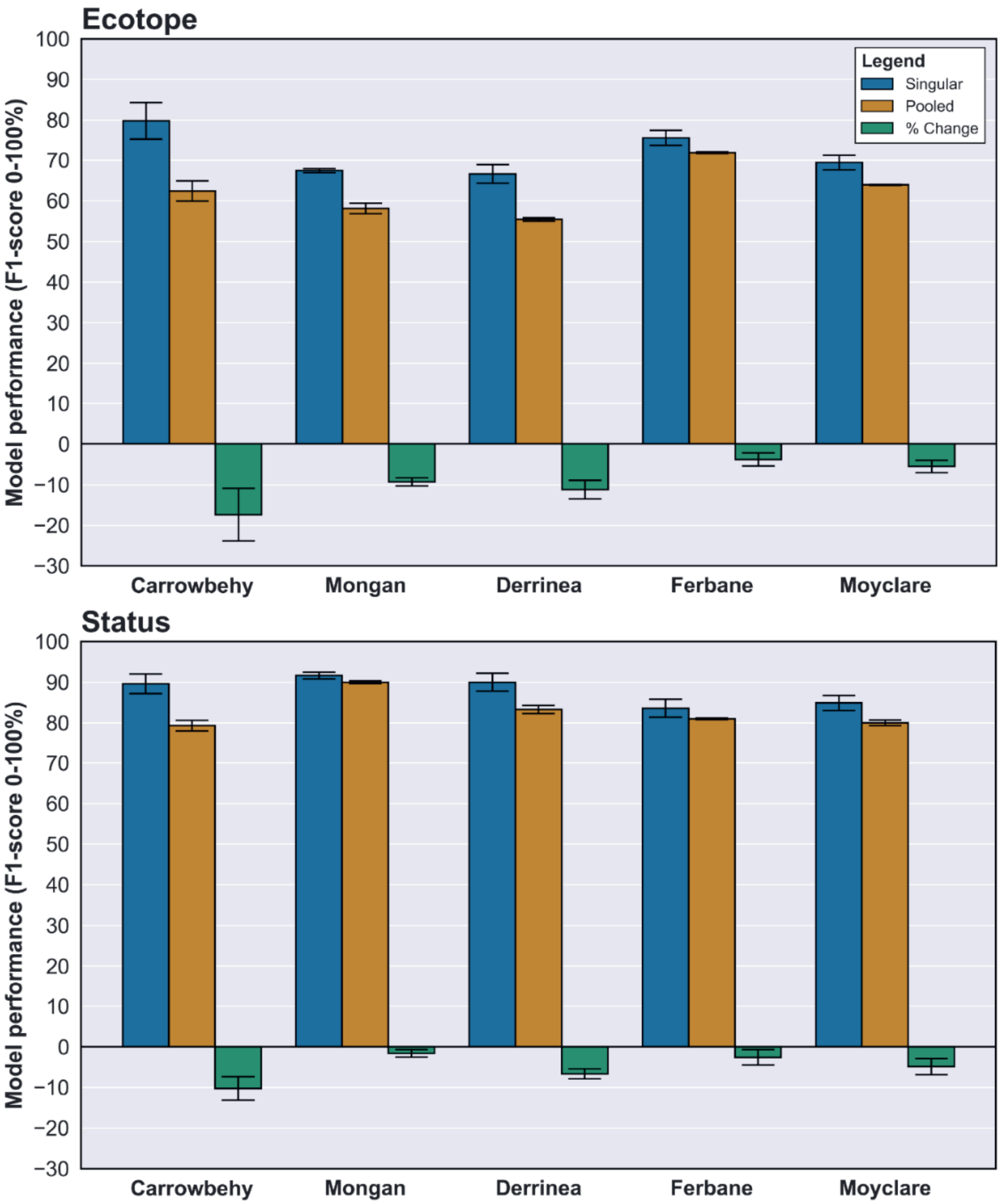


Figure 5.3 Example habitat classifications for Carrowbehy. For classified habitat maps of all peatlands, see Figure S5.28–S5.32. Represented are: **A)** orthomosaic retrieved from stitching the drone imagery of Carrowbehy, **B)** the original polygon-shaped and field-based habitat map from the National Parks and Wildlife Service (NPWS), **C)** classified ecotope map with singular (peatland-specific) ground-reference dataset, **D)** misclassified ground-reference samples for singular ecotope classifications with NPWS ecotope map outlined in white, **E)** classified status map with singular ground-reference dataset, **F)** classified ecotope map with the pooled ground-reference dataset from the four other studied peatlands, **G)** misclassified ground-reference samples for pooled ecotope classifications with NPWS ecotope map outlined in white, and **H)** classified status map with the pooled ground-reference dataset from the four other studied peatlands. Overall F1-scores (0–100%) for each classification result from the Support Vector Classifiers (SVC).



Ecotope

Status

Figure 5.4 Bar graphs visualizing overall classification (i.e. model) performance (F1-score; 0–100%) as well as change in classification performance for singular and pooled classifications of ecotopes (left) and status (right) in all of the five studied peatlands. Error bars represent variation in classification performance for each of the five folds used in cross-validation of the Support Vector Classifiers. Peatlands are sorted in order from most intact (Carrowbehy) to most degraded (Moyclare).

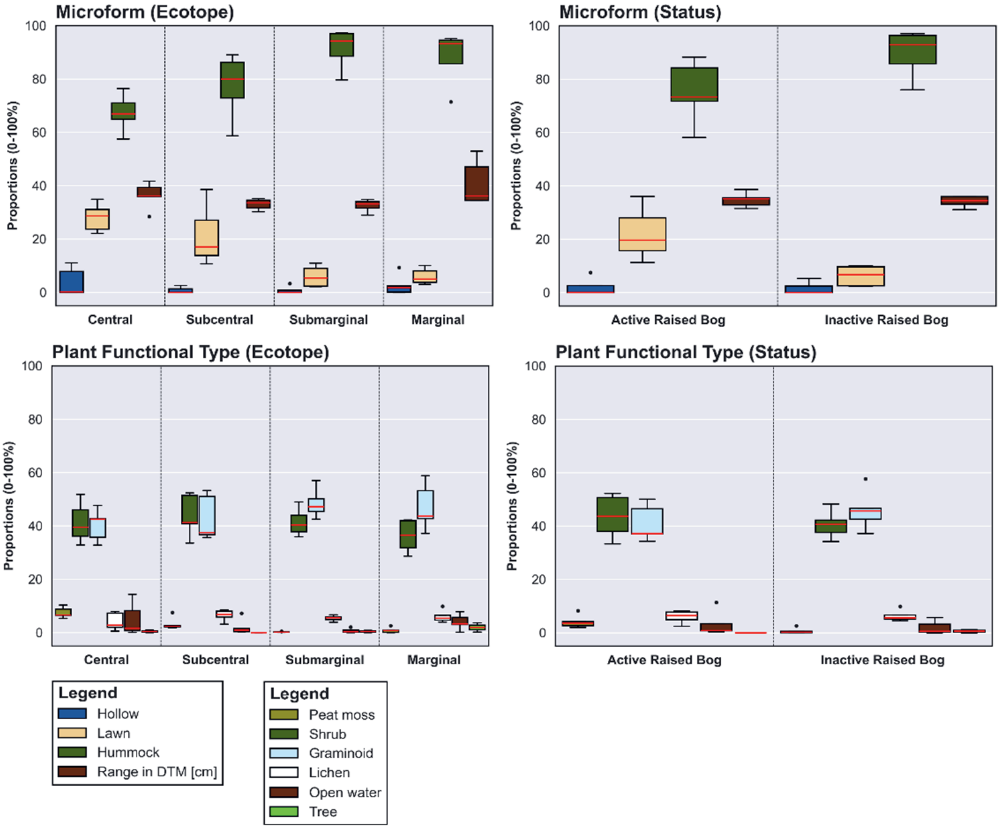


Figure 5.5 Boxplots highlighting the distribution and variability in median proportions of microforms (left) and plant functional types (right) and range in detrended Digital Terrain Model (DTM) values (surface topography) for specific peatland habitats (ecotopes left, status right) over all five of the studied peatlands. DTM values are presented in centimetres [cm] on the same y-axis as microform proportions because both ranged between 0–100. The number of samples for each boxplot represents the number of studied peatlands (*n* = 5), and therefore the median, cap and interquartile values of each boxplot correspond with the value for each individual peatland. Exception to the latter is the proportion of tree, which only occurred in Ferbane and Moyclare.

5.4 Discussion

5.4.1 Ecotope and status classifications

There is increasing need for accurate, efficient, and standardised mapping of peatland functioning and associated services to understand the effect of restoration efforts account for related investments (Andersen et al., 2017; Minasny et al., 2023; Reed et al., 2022). While habitat monitoring was traditionally carried out by the Irish National Parks and Wildlife Service (NPWS) every 6 years using a field-based approach, our results show that peatland habitat distribution (ecotopes) and habitat quality (status) can already be mapped at the peatland-scale with the use of fine-scale vegetation classifications retrieved from drone imagery. Particularly, our maps aligned for 72–88% (F1-score) with conventional maps from the NPWS. Overall model performances were also generally consistent over all studied peatlands, suggesting that mapping accuracy was not affected by differences in eco-hydrological integrity of our studied peatlands per se. Combining these findings with the rapid upcoming development and standardisation of drones for science practices in spatial ecology (Anderson & Gaston, 2013; Dronova et al., 2021; Manfreda et al., 2018), drone-based approaches could potentially replace traditional ecotope and status monitoring on the peatland-scale.

However, drone-based mapping remains limited in spatial coverage, with upper limits of approximately 1000ha per day (Steenvoorden & Limpens, 2023). Consequently, when mapping increasingly larger spatial scales, its predominant role will likely be in training, testing, validating and calibrating coarser spatial resolution but larger-scale satellite imagery with so-called nested or hybrid approaches (e.g. Bhatnagar et al., 2021; Riihimäki et al., 2019). Besides, even with our mapping approach, the notably lower classification performance at the peatland margins in the more degraded peatlands in our study warrant addressing. The lower model performance for ecotopes was likely an artifact from gridding the polygon shaped vegetation map as ground-reference dataset but also relates to the vegetation proportions between the four ecotopes in our study being more subtle and therefore more difficult to classify than the two status classes. In the upcoming paragraphs we address sources for misclassification and suggest directions for future improvements.

5.4.1.1 Alignment between conventional and drone-based mapping approaches

We created drone-derived ecotope and status maps using the proportions of the fine-scale vegetation and range in detrended digital terrain model (DTM) in 20x20m grid cells, simulating the minimum mapping unit of the field-based approach adopted for the habitat maps of the NPWS. Even though the NPWS also used a grid to identify habitat classes in the field, the resulting maps from the NPWS still follow a relatively concentric pattern from peatland centre to margin, with only few mapping units being mapped as one ecotope within the bigger boundary of another ecotope. However, field observations and remote sensing ground-reference data suggest that true habitats may be less uniform than suggested by the NWPS maps and may be closer to the drone-derived maps that display a more eccentric (pixelated) pattern throughout the studied peatlands, especially using pooled ground-reference datasets (see 4.3). Here, many individual 20x20m grid cells of one ecotope can exist within a bigger area of another (see also Figure 5.3; Figure S5.28–S5.32).

Using the concentric polygon-shaped ecotope maps from the field-based method of the NPWS as a ground-reference map for the remote sensing approach could have affected overall classification performance in two predominant ways. First, some of the gridded 20x20m labels associated with one ecotope may have belonged to another ecotope in the first place. This effect is particularly harmful if small 20x20m patches of a marginal ecotope are situated within a central ecotope and vice versa because these mislabelled cells more strongly impact the proportions of microforms and plant functional types associated with a specific habitat class than adjacent ecotopes. Second, there were many cases at the boundaries of each ecotope in the polygon-shaped NPWS map where a majority label for a 20x20m grid cell was imperfectly assigned to a habitat class. For instance, if a 20x20m grid cell was covered for 51% by central and 49% by subcentral ecotope, it would be labelled as central ecotope even though the proportions of microforms and plant functional types as well as the range in DTM within this grid cell do not fully match those of a grid cell that would occur in the core of a larger body of central ecotope. Indeed, most misclassifications between ecotopes occurred among adjacent habitat classes (Table S5.6; Figure S5.28–S5.32). Besides, misclassifications for both ecotope and status occurred significantly closer to a habitat class boundary (Table S5.10), either at the peatland margins where artificial landscape features deviating from natural marginal conditions confounded the support vector classifiers (SVC), or at a habitat class boundary in the concentric NPWS map.

Our findings highlight that classification models using a gridded and more eccentric approach for mapping can suffer notably in performance when following a more concentric map as ground-reference. This is especially true when vegetation patterns in the field are also more eccentric, such as in the more degraded peatlands in our study. Going forward, we therefore argue that the most robust, standardised, and efficient way of categorizing gridded ground-reference labels through fine-scale drone-derived imagery products is developing a rule-based decision tree before classification that assigns labels of peatland habitats to user-defined proportions of specific vegetation classes and microtopographical gradients (see also 5.4.3). This also allows a potential user to assess the optimal grid size for distinguishing between peatland habitats, which may vary between peatland types. The extremely high spatial detail of drone-derived habitat maps becomes particularly crucial here if the size of specific habitats is below the current spatial resolution of freely available satellite imagery like Landsat-9 (30m) and Sentinel-2 (10–20m), or if the spatial organisation of habitats cannot accurately be represented by rectangular pixels of the same spatial resolution.

5.4.1.2 Mapping below-canopy peat moss cover

One of the largest drawbacks of drone-based vegetation mapping with respect to field-based mapping is the inability to look below the vegetation canopy. As a result, the absolute proportions of fine-scale vegetation types associated with a specific peatland habitat class will most often differ between field-based observations and a remote sensing-based classification. We observed this in our study as well, because the grid cell with the highest proportion of peat moss in the central ecotope of our peatlands ranged between 25–45%, even though the proportion of peat moss in central ecotopes is often estimated at 90–100% with field-based measurements. This effect is not inherently detrimental to the general mapping approach because relative proportions of vegetation types generally shift consistently with what is visible from above. For example, even if the proportion of peat moss in a central ecotope as observed from drone imagery is lower than field-based observations, it will still be relatively higher than the visible proportion of peat moss in a subcentral or submarginal ecotope. Nevertheless, it is crucial to evaluate, gain understanding, and adjust the absolute differences between both methods before assigning habitat labels to specific vegetation proportions, because lacking information about below-canopy peat moss cover can still be impactful on classification performance. For instance, in some of the vegetation complexes of subcentral ecotopes, peat moss is mostly covered under tall heather and *Cladonia* lichens (Fernandez et al., 2014). Besides, the distinction between submarginal and marginal ecotope is partially related to peat moss cover that generally does not occur in extensive lawns like in the central and subcentral ecotopes, but also by peat moss that is predominantly covered by other types of vegetation. However, Given the already high importance of top-of-canopy peat moss cover as a predictor variable in determining ecotopes and status in all studied peatlands (Figure S5.13–S5.22), a future challenge is therefore to develop methods that can estimate below canopy peat moss cover based on predefined predictor variables or post-classification retrieved surrounding vegetation characteristics. This will ensure that the potential effects of missing below-canopy peat moss cover is minimized.

5.4.1.3 Developing accurate canopy height models

Classifications for Ferbane and Moyclare (the only peatlands with notable tree cover) highlighted that tree cover was an important predictor variable in distinguishing ecotopes for those peatlands. This highlights that tree cover as a predictor variable could potentially compensate for the lack of open water especially in these peatlands that are more degraded. This effect was expected theoretically because tree encroachment due to surface drying in these Midland raised bogs generally happens inwards from the peatland margins. However, an exception is Annex I priority habitat ‘bog woodland’ (91D0), which is a very wet habitat type occurring in the middle of a bog, often with high peat moss cover. While classification performance for trees was high in both peatlands (90% and 96% respectively), misclassifications were often false positive with shrubs and graminoids in more central areas of the peatland (Table S5.5). Such misclassifications are particularly harmful in these habitat classification models because they give the incorrect impression that trees are scattered evenly throughout the peatland, even though they are a potentially valuable indicator of central versus marginal habitat classes for both ecotopes and status, particularly in more degraded peatlands. Given the flexibility of drones, we therefore suggest inclusion of a canopy height model in future studies where possible especially if spectral reflectance of vegetation types with contrasting traits and function are relatively similar. However, in peatlands this initially requires adaptive point-cloud processing and ground-validation with a very-high resolution GPS due to their generally dense vegetation cover, which otherwise leads to severe overestimation of modelled terrain compared to field measurements (Lovitt et al., 2017; Y. Berger Barnett, personal communication, 21 May 2024). Yet, eventual inclusion of an accurate canopy height model as a predictor variable in classification models will most likely be highly valuable in distinction between vegetation classes with contrasting functions but overlapping spectral reflectance curves like trees, shrubs, and graminoids.

5.4.1.4 Distinguishing between natural and artificial landscape features

The maps resulting from both our fine-scale vegetation classifications and habitat classifications show that artificial landscape features within the margins of the studied peatlands have had a notable effect on classification performance at the margins. Particularly, while most misclassifications for ecotopes occurred between adjacent classes from peatland centre to margin, some samples from the ground-reference dataset were misclassified as an ecotope representing a completely different hydrological condition. Here, features like dammed drainage ditches, artificial pools, blocked drains, cutovers, and excavator tracks simulated environmental conditions at the peatland margins that would naturally occur mostly in the peatland centre. This diminished separability of habitat classes, especially when compared to the more pristine peatlands in our study. For instance, open water pools generally only occurred only in the intact central areas of our studied peatlands, but the artificial pools created by excavators to fill drainage ditches resulted in mapped areas of open water at the peatland margins as well. Interestingly, however, the presence of artificial pools at the peatland margins improved classification performance in Ferbane because this peatland contained no natural open water pools in the peatland centre. Besides, compaction of peat due to the weight of the excavators occasionally resulted in large linear patches of lawns at the peatland margins in Ferbane and Moyclare. Lastly, peat dams, drainage ditches and cutovers at the studied peatlands' margins often simulated a range in microtopographical gradient that is normally only observed in large hummock–hollow complexes in a peatland centre. This likely also explains the unexpectedly low added value of the microtopography predictor variable in distinguishing between peatland habitats (Figure S5.13–S5.22). Given the relatively concentric and convex morphology of most peatlands in our study area and worldwide, adequate derivation of their macro-topography could also be used in classification of habitats in future studies as it is such a strong driver of broader water level, nutrient supply, and drainage (Schouten, 2002; van der Schaaf, 2002).

Our results show that habitat classification performance and resulting mapping accuracy was affected by the presence of artificial landscape features, giving rise to the idea that mapping accuracy decreases the more human impact a peatland has had. However, the presence of artificial landscape features should not necessarily be an issue for development of a standardised mapping approach for peatland habitats, especially because mapping and monitoring of habitats often occurs in peatlands that are at least partially degraded, particularly in the European Union. Rather, understanding the role that artificial landscape features have on mapping accuracy is crucial in developing habitat classification approaches, as it allows for development of new predictor variables and methods that can potentially distinguish artificial features from natural peatland features where needed, such as recent studies identifying drainage ditches within degraded peatlands (Carless et al., 2019; Robb et al., 2023). This may only serve to improve the mapping accuracy of peatland habitats in the future, both between different peatland types, as well as in similar peatlands differing in eco-hydrological integrity.

5.4.2 Further improvements in microform and plant functional type classifications

Microforms and plant functional types were classified and mapped with high accuracy in all studied peatlands, with model performance (F1-scores) of 96% and 93% respectively. Nevertheless, inconsistencies and inaccuracies in the resulting maps highlighted several recurring spatial patterns that warrant addressing in similar future studies, especially because resulting maps of fine-scale vegetation patterns are used as input predictor variables for subsequent classifications of habitats in our study.

5.4.2.1 Importance of an adequate segmentation approach

Adequate segmentation is the key to accurate geographic object-based image analysis (Blaschke et al., 2014). Yet, the challenge with segmenting remote sensing imagery of natural ecosystems is that it is difficult to know a priori which segmentation approach best represents their patterns in the field (Räsänen et al., 2013), particularly because many segmentation algorithms face difficulty with defining appropriate parameters for the plethora of different fields and spatial levels of detail in which they are used (Blaschke et al., 2014; Hossain & Chen, 2019). In fact, the most feasible option is often to carry out a multitude of classifications using various relevant segmentation algorithms and parameters and compare their effect on classification performance to choose the most optimal combination of parameters. We already explored optimization of two different segmentation algorithms (Quickshift and SLIC) in mapping fine-scale vegetation patterns through an initial sensitivity analysis on their parameters in this study. Yet, visual interpretation of even the most “optimal” segmented drone imagery for each peatland still occasionally showed inconsistencies where individual plants and patches of vegetation and open water were erroneously merged from or split into unique segments. Incorrect segmentation resulted in under- or overrepresentation of specific vegetation classes in specific areas of a peatland. Accordingly, we still need better understanding on the effect of segmentation parameterisation on the patch metrics (i.e. size, shape, and spatial organisation) of resulting segments, as well as the pros and cons that different segmentation approaches have for mapping specific types of vegetation. Given the large variety in segmentation approaches available, and their important role in classification performance, we argue that at the bare minimum, studies using object-based image classification to map peatland vegetation document their segmentation approach with more detail.

5.4.2.2 Inclusion of infrared imagery

The results of our classifications showed that the combination of red-green-blue (RGB) imagery, the RGB-derived Hue-Saturation-Value (HSV) colour model, and detrended DTM (surface topography) were often highly effective in mapping all vegetation classes in our study. However, the confusion matrices developed from the classifications highlighted that vegetation classes with contrasting ecological requirements were occasionally still misclassified as one another. For instance, some commonly occurring misclassifications were between hollow and hummock, graminoid and lichen with open water, and peat moss with graminoid (Table S5.4–S5.5), resulting in under- or overrepresentation of these classes in some areas throughout the peatland. Given the importance of peat moss and open water in determining between more central and marginal habitat classes in the classification models (see also Figure S5.13–S5.22), misclassifications of these fine-scale vegetation classes had cascading effects on the accuracy of the resulting habitat maps. To mitigate and potentially eliminate this issue, inclusion of near-infrared (NIR) imagery in classification approaches for peatland vegetation may be highly valuable, as was already highlighted by several previous studies (e.g. Beyer et al., 2019; Knoth et al., 2013; Räsänen et al., 2020; Simpson et al., 2024), particularly because peat moss exhibits distinctly differens spectral signatures in the NIR portion of the colour spectrum compared to other peatland vegetation types (Bubier et al., 1997; Pang et al., 2020; Schaepman-Strub et al., 2009; Simpson et al., 2024). While most consumer-grade drones do not contain a NIR sensor by default, an increasing number of newly released consumer-grade drones include NIR sensors at reasonable prices, and we therefore strongly recommend their inclusion for future drone studies aimed at mapping peatland vegetation whenever possible.

5.4.2.3 Accounting for plant phenology

Plant phenology has shown to be a crucial factor affecting classification accuracy in ecosystems with strong seasonal phenological dynamics like peatlands (Cole et al., 2014; Cruzan et al., 2016; Dudley et al., 2015; Halabisky et al., 2018). Although we did not formally analyse the effect of plant phenology on spectral separability in our study, we did observe its adverse effects in our imagery and classification results. For instance, because our imagery was taken at the end of the growing season, the characteristic purple flowers of common heather (*Calluna vulgaris*) had already partially turned orange because of flower senescence, especially at the margins close to the peatland cutover where surface conditions are drier. Besides, various graminoids had started drying out (grass senescence), resulting in whiter spectral reflectance like lichen. Yet, spectral differences among peat mosses and between peat mosses and other plant functional types generally increased over the course of the growing season. Nevertheless, the observed variability in plant phenology over the peatland-scale resulted in notable areas with misclassifications in all studied peatlands (Figure S5.23–S5.27), predominantly at the peatland margins where dense patches of common heather with bright red/orange senesced flowers were confused as lawn and peat moss for classifications of microforms and plant functional types respectively. Researchers should take advantage of the flexibility of drones to conduct flights during time-periods of the year when phenological stages of studied plants are most optimal for their identification and differentiation.

5.4.2.4 Refining digital terrain models and derivatives at peatland-scale

The results of our study emphasized the benefit of using a drone-derived DTM as predictor variable in mapping fine-scale peatland vegetation. Particularly, the mean value of the detrended DTM was among the most important predictor variables for classification of both microforms and plant functional types in all the five studied peatlands (Figure S5.3–S5.12). While the detrended DTM was accurate in most situations, we did consistently observe several cases with errors in the developed detrended DTMs throughout the studied peatlands that warrant addressing. For instance, the homogeneity and depth of some water bodies resulted in poor estimation and interpolation of the DTM. When such pools were also partially filled in with peat moss, the segments that these pools were associated with were often mistaken for a lawn or hummock. Furthermore, the detrended DTM exhibited a notable visual decrease in accuracy at the far margins of the peatland. This can be attributed to a sudden elevation drop resulting from cutovers. As a result, the microtopography of areas surrounding the cutover was poorly estimated through our detrending method and was mostly much lower than the true value in the uncorrected DTM. This led to large patches of shrubs at the margins being misclassified as lawn and graminoid in microform and plant functional type classifications respectively. Lastly, the detrended DTM was also inaccurate in Derrinea because till mounds and drumlin features created notable variations in topography. Besides, the peatland slopes down heavily towards a nearby river on the north and east side of its margins. As a result, both the areas surrounding the edge of the glacial features as well as the downwards sloping areas of the peatland were incorrectly categorized as hollows even though they were hummock dominated. Because of the generally domed shape of raised bogs from centre to margin, detrending of a DTM is practically a requirement in classification approaches utilizing microtopography on the peatland-scale. For this reason, and because the DTM is a crucial predictor variable in accurate characterization of microforms and plant functional types and therefore habitats, there is need to expand on the fairly generic moving-window averaging approach that was used to detrend the DTM in this study. This ensures that topography is accurately represented in all peatlands regardless of their topographical complexity, invariably improving future mapping accuracy of both fine-scale vegetation and habitats. Besides, we only used the mean value of the detrended DTM (topographic position index) as an input predictor variable in our mapping approach. While this resulted in notable increases in accuracies compared to permuting the variable in an initial exploratory analysis, the use of additional derivate topography predictor variables like slope, curvature, it may be warranted in future studies for distinguishing between specific vegetation types, as other studies have shown their added value (e.g. Kaneko et al., 2024; Räsänen, Aurela, et al., 2020; Räsänen et al., 2019). This is particularly true because vegetation types are so tightly linked to water and nutrients, which in turn are driven by peatland topography.

5.4.2.5 Stricter consideration of flight conditions

Weather is well-known to affect the quality of drone-derived imagery, where cloud cover and the position of the sun can strongly influence ambient light and shadows when a flight is carried out. This can not only impact the quality of the resulting imagery, but also introduce notable variation in subsequent estimation of predictor variables resulting from the imagery (Assmann et al., 2019). Although we aimed to minimize the introduction of variation in light conditions and shadows in the imagery by flying within one hour of solar noon and on mostly clouded days only, there was some introduction of variation because of the presence of scattered cumulus clouds on the days where we captured drone imagery for Derrinea, Mongan, and Ferbane. While this resulted in negligible overexposure at the margins in Mongan and Ferbane. the colour orthomosaic from Derrinea contains several larger areas of both overexposure and severe shading. We did not perform a systematic evaluation on the effect of these factors on classification performance, but we did visually observe that areas within the overexposed areas were often misclassified as lichen and lawn, and that shaded areas were often misclassified as shrub or hummock. This might explain the comparatively low classification performance of microform, plant functional type and habitats in Derrinea with respect to other peatlands. While radiometric calibration can certainly be performed to minimize some of this variation, this becomes more difficult and time-consuming to carry out when mapping at the peatland-scale. Besides, we performed histogram matching of the affected area with an unaffected reference dataset within the peatland to colour balance the orthomosaic, but this did not result in removal of all overexposed and shaded areas. Given the flexibility of drones, we argue stricter consideration of flight conditions is more feasible, carrying out flights only on fully clouded days to minimize the potential introduction of variation through weather conditions as we observed in our study.

5.4.3 Towards standardised and transferable peatland habitat mapping

Our results show that spatial transferability of the mapping approach was limited, because using pooled ground-reference datasets for classifications of peatland habitats decreased model performance with 5% for status and 10% for ecotope maps. The results from our study showed that the proportions of microforms and plant functional types as well as the range in detrended DTM that correspond to a specific habitat class differed per peatland, which severely hampered upscaling between peatlands in our study (Figure 5.5; Figure S5.33–S5.34). While this effect may at least partially be explained by some relativity when assessing the vegetation proportions corresponding to specific habitat classes among peatlands in the field, or misclassifications of microforms and plant functional types at each peatlands' margins (see 4.2), it is most likely also affected by using the relatively concentric field-based ecotope map from the Irish National Parks and Wildlife Service (NPWS) as a ground-reference map for classification of habitat types (see 4.1). This could have resulted in smaller mapping units being overlooked or excluded within the core of a bigger mapping unit. We observed this effect in our study as well because the ecotope maps using pooled ground-reference datasets were often more eccentric than the peatland-specific maps, which largely followed the concentric pattern of their corresponding NPWS maps. This is fairly logical particularly considering that models using pooled ground-reference datasets were not trained on the peatland to be classified, and therefore were not dependent on potentially mislabelled habitat classes resulting from using the peatland-specific NPWS maps as ground-reference. Consequently, even though the performance metrics of the pooled maps are consistently much lower than those of the peatland-specific maps, the pooled maps may actually be more robust than their peatland-specific counterparts because in reality habitats are more eccentric than may seem from the NPWS maps, at least in our studied peatlands.

Irrespective of the causes, it is crucial for upscaling and standardised monitoring of peatland habitats that the vegetation characteristics that define specific peatland habitats are also standardised at least over multiple peatlands and peatland types. Our results show this was currently the main factor for hampering spatial transferability. Depending on the goal of the study, as well as time, resources, and type of imagery that are available, we suggest three solutions to achieve this. First, one can develop, improve and/or utilize additional remotely sensed predictor variables that lead to better and more consistent distinguishment between fine-scale vegetation types and habitats among peatlands (see 4.1 and 4.2). Second, one can standardise the values of predictor variables that co-determine specific peatland habitat classes through a rule-based categorisation system (see 4.1.1). Lastly, one can adjust the number and spatial scale of the relevant habitat types to be mapped. Although this reduces spatial detail, it amplifies distinguishability of residual habitats, which may ultimately improve overall mapping accuracy. Particularly, our study shows that status (active versus inactive raised bog only) can already be mapped with sufficient accuracy to evaluate spatiotemporal dynamics in their extent and functions. However, more accurate maps of ecotopes are still needed in order to act as an ecological indicator, especially because functions like carbon sequestration can vary notably between different ecotopes (Regan et al., 2020; Swenson et al., 2019). Overall, the results from our analyses and the recommendations in this discussion section serve as a starting point from which future drone studies can build to further optimize and standardise mapping and monitoring of vegetation patterns in a wide variety of peatlands and peatland types. The potential use of such vegetation maps as ecological indicators for peatland functions will not only help to us to better assess the effect of implemented restoration efforts and related investments, but also help us better understand the vulnerability of peatland functions to predicted changes in climate and land-use in the 21st century.

5.5 Conclusion

The results of our study show that fine-scale vegetation patterns and habitats can be classified accurately and consistently on the peatland-scale using drone-derived imagery products and machine learning classifications. However, while status is already mapped adequately to allow for evaluating their spatiotemporal dynamics, more accurate maps of ecotopes are still needed, especially if such maps are applied in matters like carbon financing schemes and restoration evaluation. Besides, peatland-specific ground-reference data is required until the vegetation characteristics that define specific peatland habitats are standardised at least over multiple peatlands of the same type. Inconsistencies in classification models for the peatlands in our study resulted largely from artificial landscape features created by restoration, overexposure and shading, suboptimal drone-derived elevation models, plant phenology, and development of a gridded ground-reference dataset from an original field-based mapping approach. We provide comprehensive and novel insights into the multiple requirements for accurate large-scale peatland vegetation mapping on which future drone studies can build to further optimize and standardise monitoring of vegetation pattern dynamics and associated functions in a wide variety of peatlands and peatland types of contrasting eco-hydrological integrity.

Chapter 6

General discussion

The overall absence of consistent documentation and comparisons of different drone-based approaches for mapping peatland vegetation patterns is currently resulting in large knowledge gaps in the requirements for accurate and efficient mapping. This is limiting the upscaling that is often required to monitor peatland vegetation patterns as ecological indicators. Besides, lack of development towards standardised workflows that can be employed or used as a starting point from which to build on are also hampering the general applicability of drones in the field. These knowledge gaps stressed the demand and responsibility for comparative testing.

I aimed to contribute to these knowledge gaps by providing novel and comprehensive insights into the strengths, limitations and requirements of drones for large-scale mapping of peatland vegetation patterns. This way, I aimed to advance the development of accurate, efficient and standardised monitoring workflows that various users can employ or build upon to assess the spatiotemporal dynamics of peatland vegetation patterns, as well as their functions and the services they provide. To this end, I developed and refined a first set-up for an accessible consumer-grade drone-based remote sensing approach that can already accurately and efficiently map plant functional types, microforms and habitats. These vegetation patterns can be mapped in a variety of peatlands and peatland types of contrasting vegetation pattern complexity and eco-hydrological integrity. Hereby I show that classifications with machine learning models can hold a leading role in mapping peatland vegetation patterns because of the efficiency by which consumer-grade drones and related photogrammetry software can capture and process all spectral, spatial and topographical information at large spatial scales and with unprecedented levels of detail. These factors were crucial in characterising vegetation patterns in this thesis.

6.1 Challenges and recommendations for drone-based mapping of vegetation patterns

Drone-based remote sensing is a new scientific discipline that has only started gaining substantial popularity in peatlands in the last decade (Abdelmajeed & Juszczak, 2024). This novelty is a driver of the current disparate and indiscriminate use of remote sensing methods in peatland mapping, as most optimal uses are still being explored, and standardised workflows are lacking. Nevertheless, drone technology is progressively evolving towards standardisation for environmental research. We are now seeing increasingly affordable drones with sensors tailored specially for vegetation mapping, high-resolution global positioning systems, improved stability, longer flight times and consistent and customisable automated flight planning. This is making drone technology in spatial ecology increasingly accessible for a wide variety of users. For these reasons, the time is now to exploit these advancements by putting more effort into developing and optimising mapping approaches that are specifically designed to evaluate their accuracy and efficiency for monitoring peatland vegetation patterns in a variety of different peatlands and peatland types of contrasting vegetation pattern complexity and eco-hydrological integrity.

Studies like this thesis that aim to elucidate pivotal aspects of drone-based remote sensing for accurate and efficient vegetation pattern mapping could certainly help move towards standardisation practices. In fact, our results already highlight that microforms, plant functional types and habitats can be mapped at large spatial scales with consumer-grade drones. Particularly, we achieved high accuracy and efficiency simultaneously in all studied peatlands of contrasting vegetation pattern complexity and eco-hydrological integrity, especially with the most current version of the mapping approach. These results can therefore be used as a baseline from which to further develop, evaluate and optimise drone-based vegetation mapping studies in peatlands and similar ecosystems with short vegetation structure. Besides, by iteratively expanding and refining the mapping approach throughout each subsequent research chapter, we were also able to identify and/or solve at least some of the numerous challenges that caused inconsistencies, inaccuracies and/or inefficiencies throughout all peatlands in the study area (Table 6.1). The question still remains what accuracy and efficiency is ultimately needed from a mapping approach to answer specific research questions and to monitor specific peatland functions. Yet, some mapping aspects within this thesis warrant addressing to ensure that at least plant functional types, microforms and habitats can continue to be mapped accurately and consistently, and that these mapping efforts can be upscaled to the spatial scales at which peatland functions related to these vegetation patterns manifest themselves.

6.1.1 Drone imagery acquisition

6.1.1.1 Flight altitude: a true example of less is more

Drone imagery acquisition is one of the first but most impactful stages of a drone-based mapping approach where combined accuracy and can disproportionally be affected. The required spatial scale for vegetation pattern mapping and therefore flight altitude requirements are at least partially dependent on the vegetation patterns at hand and the associated functions under investigation. Still, I found that while previous studies in peatlands flew on average at 68m altitude, and none higher than 110m, these studies often lacked a clear rationalisation for their chosen flight altitude (e.g. Assiri et al., 2023; Bertacchi et al., 2019; et al., 2019; Bhatnagar, Gill, & Ghosh, 2020; Ikkala et al., 2022; Iljas, 2022; Kalacska et al., 2021; Knoth et al., 2013; Lehmann et al., 2016; Lendzioch et al., 2021; Lopatin et al., 2019; Palace et al., 2018; Simpson et al., 2024). Some studies did not even mention their flight altitude at all.

Our findings show that flying at 120m altitude (maximum legal flight altitude) still results in drone imagery with spatial resolutions of 2.7cm. This translated into equally accurate and consistent maps as at 20m flight altitude. Yet, our overall mapping approach at 120m flight altitude was 19–22 times faster than at 20m flight altitude, while data volumes decreased a factor 50 (Chapter 3). Going forward, using otherwise identical flight and image processing parameters, flying at the maximum legal altitude of 120m is near always the most optimal approach for mapping fine-scale vegetation patterns in peatlands and in other ecosystems like moorlands, heathlands and tundra that share similar short-structured and heterogeneous vegetation patterns. However, imagery at lower flight altitudes could be useful in case of ground-referencing and validation of vegetation patterns in the field (see also 6.1.4).

6.1.1.2 Overlap requirements for accurate imagery products

Sufficient forward- and side-overlap is required to be able to stitch imagery together and to create point clouds for photogrammetry that are dense enough to accurately estimate the underlying surface. However, overlap requirements for both orthomosaics and digital elevation models in peatlands have hardly been evaluated extensively and statistically if at all. Yet, minimum overlap requirements are not only a large potential driver in facilitating upscaling of drone-based vegetation pattern mapping approaches to the peatland-scale, but these differ notably from ecosystem with less vegetation cover than peatlands (Y. Berger Barnett, personal communication, 21 May 2024). Most drone-based studies that use photogrammetry in peatland vegetation mapping used extremely high forward- and side-overlap percentages at least above 75% (e.g. Beyer et al., 2019; Bhatnagar et al., 2020; de Roos et al., 2018; Ikkala et al., 2022; Kalacska et al., 2017; Simpson et al., 2024). These studies do this with the argument that such overlap percentages are a necessity for accurate drone imagery products. Yet, just like with flight altitude, some others do not even mention their defined overlap percentages at all.

To evaluate minimum overlap requirements and its role on efficiency of drone imagery acquisition at larger spatial scales, we performed a pilot experiment in the Bargerveen, a peatland in the Netherlands, in May 2022. Here, we performed five flights in an area of 4ha using various overlap percentages (50–50, 60–60, 75–50, 75–60, and 80–80 forward- and side-overlap), and visually compared its effect on the quality and intactness of the imagery products. This experiment showed that forward- and side-overlap percentages of 50% were sufficient to develop an orthomosaic that visually mirrored one that was developed using 80% overlap. However, adequate digital elevation models were only developed using 75–60% and 80–80% forward- and side-overlap. These requirements are in line with the general consensus for photogrammetry in terrestrial ecosystems (Singh & Frazier, 2018). Although we did not validate the absolute accuracy of the digital elevation models in the field using, models using 75–60% forward- and side-overlap seemed satisfactory for the purpose of extracting relative topographical position, we used these flight parameters for subsequent drone surveys (Chapter 4, 5).

While our drone flights at 120m altitude with 80–80% forward- and side-overlap from Chapter 3 captured imagery at a rate of about 42sec/ha per hectare, flights of whole peatlands using 75–60% forward- and side-overlap captured imagery about four times faster at 10sec/ha. When mapping smaller study areas, using conservatively high overlap percentages (e.g. >75%) is most suitable to avoid running the risk that imagery from a flight is inadequate for development of subsequent imagery products. However, the increase in flight duration from using high overlap percentages has implications for power supply and data volumes that may inhibit upscaling of vegetation pattern mapping to the peatland-scale.

For this reason, additional studies are needed to ascertain the effect of image overlap on the accuracy of orthomosaics and digital elevation models in peatlands so this parameter can be optimised in future drone-based vegetation mapping studies. This ensures vegetation pattern mapping can realistically be expanded to the largest areas possible if and where needed.

6.1.2 The value of additional camera sensors

Multiple drone studies in peatlands and other short vegetation structure ecosystems have shown that inclusion of additional camera sensor types such as hyperspectral, near-infrared (NIR), thermal and LiDAR can improve distinguishability of different vegetation patterns (e.g. Beyer et al., 2019; Cao et al., 2018; Cole et al., 2014; Kalacska et al., 2017; McPartland et al., 2019; Sankey et al., 2018). However, other peatland drone studies highlight that such sensors do not always lead to notably improved classifications of vegetation (e.g. Harris et al., 2015; Putkiranta et al., 2024; Räsänen et al., 2020), and that photogrammetry-derived digital elevation models were of equivalent or even better accuracy than those developed through LiDAR (Czapiewski, 2022; Kalacska et al., 2021; Lovitt et al., 2017; Mercer & Westbrook, 2016). Still, most of these studies did not perform comparative testing to assess where and when additional camera sensors did or did not outperform imagery in the visible spectrum (RGB). Inclusion of additional camera sensors or not is critical from the perspective of efficiency as I defined in section 1.6, because implementing additional camera sensors into drone-based mapping approaches is not at all so straightforward as simply acquiring and installing the sensor.

Specifically, additional sensors result in extra costs, time, complexity and computational requirements for both data collection and image processing. This is because payloads may need to be installed, and new and diverse types of imagery need to be captured and processed into workable and meaningful datasets for vegetation pattern mapping. We already ran into considerable issues with computational power using only raw spatial resolution RGB imagery (three spectral bands) at spatial scales larger than a few hectares. Yet, hyperspectral camera sensors generate enormous amounts of data, since they retrieve spectral information in hundreds of narrow spectral bands which all have similarly high spatial resolution as RGB imagery. Besides, these sensors need to be recalibrated regularly (Adão et al., 2017; Pablo Arroyo-Mora et al., 2019; Soffer et al., 2019). The high dimensionality of hyperspectral data subsequently demands consideration of many technical aspects to allow for adequate processing, such as available hardware and software, data compression and data types, implementation of extremely efficient algorithms and data dimensionality reduction (Burger & Gowen, 2011). This complexity is a main driver of the small number of hyperspectral studies in many ecosystems (Abdelmajeed & Juszczak, 2024; Adão et al., 2017), which in turn results in a lack of standardised workflows that users can follow for accurate and efficient data processing. Similar to hyperspectral data, LiDAR tends to be much more costly compared to drone-based photogrammetry, which is due to the additional and specialised components and advanced technology it requires for image acquisition and image processing. LiDAR does have the possibly to penetrate dense vegetation canopies, which is arguably the most beneficial and valuable aspect of LiDAR over photogrammetry.

The abundance of peat moss is often seen as a key indicator of peatland functioning (Vitt & House, 2021), peatland resilience (e.g. Harris et al., 2020; Rydin & Jeglum, 2013; Turetsky et al., 2012), and restoration success (González et al., 2014; Haapalehto et al., 2011; Rochefort et al., 2013; White et al., 2020). Similarly, open water pools are an important driver of carbon fluxes in peatlands where they are present (Pelletier et al., 2015; Taillardat et al., 2024), but are also indicative of the water table (Rahman et al., 2017) and habitat diversity (Steenvoorden et al., 2024). Consequently, misclassifications that lead to overrepresentation or underrepresentation of these crucial vegetation pattern classes in specific areas could have cascading effects on assessments of peatland functions or on habitat classifications that depend on their proportions as predictor variables, as was often the case in Chapter 5. To mitigate and potentially address this challenge, multiple studies have shown the benefit of drone-based NIR imagery in distinguishing vegetation pattern classes like peat moss and open water in situations which would otherwise lead to low spectral separability (Beyer et al., 2019; Knoth et al., 2013; Räsänen, Aurela, et al., 2020; Simpson et al., 2024). Besides, improved distinguishability of vegetation pattern classes that are sensitive to NIR predictor variables may ultimately improve the distinguishability of all mapped vegetation pattern classes. This highlights inclusion of NIR imagery as an example where specific circumstances may call for specific measures (see also 5.4.2.2).

Research-grade drones with additional sensors may provide valuable additional information to a mapping approach, but their costly, complex, computationally heavy and time-consuming nature is often a barrier to multiple user groups. This can in turn limit the general accessibility and efficiency of drone-based remote sensing. The results of this thesis highlight that predictor variables which were computed with RGB imagery and photogrammetry-derived topography were often adequate to distinguish most vegetation patterns in the study area from one another (Chapter 2, 3, 4, and 5), and only failed in specific circumstances. Considering these factors, the inclusion of additional sensors requires much more comparative testing on the role of specific sensors in improving mapping accuracy of specific vegetation patterns in different peatlands, peatland types and unique circumstances. NIR imagery may be an exception to this rule because it adds only one extra band of information, its sensor can increasingly affordably (<€4500) be integrated into existing consumer-grade drone types, and it shows clear added value in discriminating between ecologically relevant peatland vegetation pattern classes. Hence, RGB imagery and photogrammetry-derived topography combined with NIR imagery wherever possible seem like the optimal choice for most vegetation pattern mapping efforts in these short vegetation structure ecosystems.

6.1.3 Processing drone imagery and deriving predictor variables

6.1.3.1 Tailoring spatial resolutions to the scales of interest

The raw spatial resolutions of drone imagery we acquired in this thesis were centimetre level up to 2.7cm at 120m flight altitude (Figure 6.1C). These raw spatial resolutions resulted in severe difficulties and complications with computational power, data volume and processing times (Chapter 2, 3, 4). In fact, the personal computer we employed always crashed when conducting the analyses at spatial scales above a few hectares (Chapter 2, 3). Besides, they also caused notable internal heterogeneity in the spectral reflectance of specific vegetation pattern classes (see also 6.1.3.3). To this end, we not only segmented our imagery (see 6.1.3.2), but also resampled our drone imagery from raw spatial resolutions of 2.7cm up to 1m (Figure 6.1E). We discovered that resampling until spatial resolutions of 0.5m for microforms and 0.25m for plant functional types before segmenting still resulted in high overall classification performances over all peatlands (Chapter 4). This was in line with Räsänen and Virtanen (2019) and Becker et al. (2008) who highlighted similar submeter spatial resolution requirements for mapping fine-scale vegetation patterns and functions in peatlands. The general conclusion that we drew from these findings is that more data is often not better when it comes to drone-based mapping of vegetation patterns in peatlands or other ecosystems with similar short vegetation structure. Particularly, using raw spatial resolutions makes upscaling beyond a few hectares extremely challenging, even though raw spatial resolutions are considerably higher than is realistically required for accurate maps of at least plant functional types and microforms (Figure 6.1; Chapter 3, 4). Still, resampling from 2.7cm to 0.25m reduced both data volumes and processing times exponentially by a factor 83 (Chapter 4). While minimum spatial resolution requirements may differ in other peatlands and peatland types, these results highlight that resampling raw spatial resolution imagery is essential to realistically enable upscaling to larger areas. Furthermore, it may also improve the spectral reflectance signatures of specific vegetation pattern classes, at least when working on a pixel-by-pixel basis.

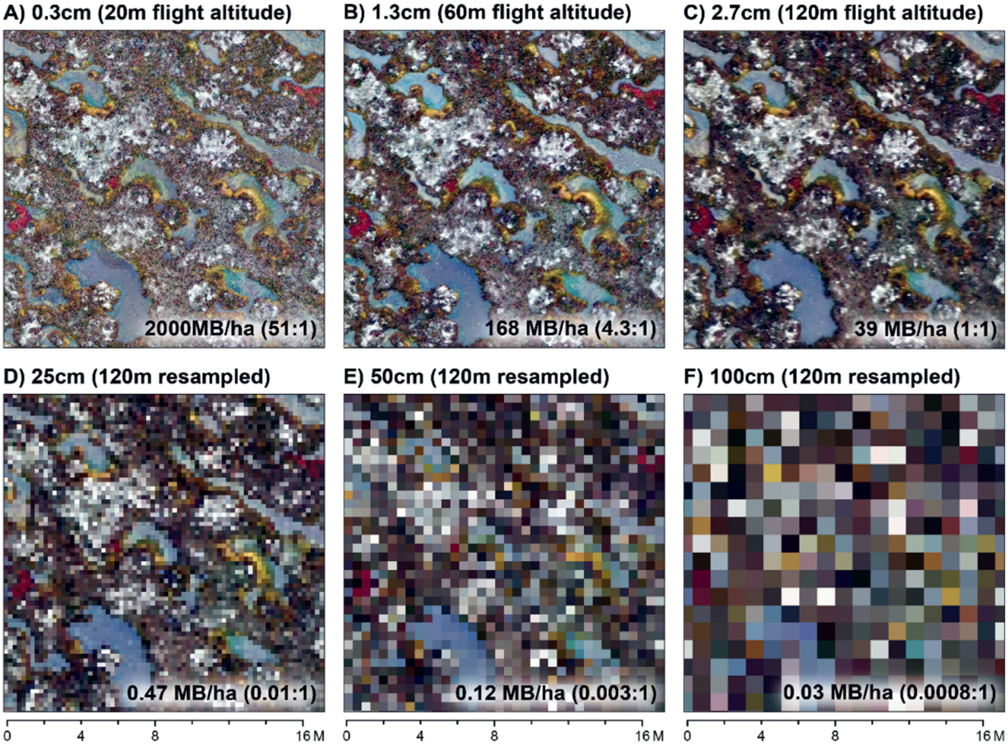


Figure 6.1 Overview of the effect of spatial resolution on the visibility of different peatland vegetation patterns in Carrowbehy bog. Visualised is a snippet of about 17x17m of the same area using imagery with spatial resolutions ranging from 0.3cm to 100cm, and highlighted in the bottom right corner of each subfigure is the data volume using the respective spatial resolution and its ratio compared to imagery of 2.7cm (analogous to flying at 120m flight altitude using a DJI Mavic 2 Pro).

6.1.3.2 Developing an adequate segmentation

We resorted to the use of segmentation in all research chapters not only to make our mapping approach more efficient (Chapter 3), but also to aggregate pixels into more meaningful and representative ecological objects for classification (Blaschke et al., 2014; Figure 6.2). Yet, optimising spatial resolutions for specific peatland vegetation patterns remained challenging in all of our research chapters because spatial resolution had direct implications on segmentation accuracy. We highlight that within segmentation there is a complex interdependency between spatial resolution, spatial vegetation characteristics, classification accuracy and efficiency (Chapter 3, 4; Figure 6.2). Segments should ideally be detailed enough that those of different vegetation pattern classes in a study area can still exhibit sufficient spatial complexity to represent their unique spectral, spatial and topographical characteristics. However, they should not be so small that overall computational demand, data volume and processing times become unmanageable in time and resources. Given the variability of vegetation patterns we already observed in our studied peatlands (Chapter 4), there is not a one-size-fits-all approach to optimising spatial resolution for adequate segmentation, and both need to be tailored specifically to individual peatlands or peatland types. These findings reveal that visual inspection of the size and organisation of vegetation patterns in the study area may help notably in planning flight campaigns and subsequent analyses more accurately and efficiently.

The success of our mapping approach depended strongly on a diligent choice of spatial resolution and segmentation algorithms and parameters, which is in line with other peatland mapping studies (Dronova et al., 2012; Räsänen & Virtanen, 2019; Virtanen & Ek, 2014; Figure 6.2). These findings highlight that segmentation is one of the most important aspects of a drone-based mapping approach for fine-scale vegetation patterns because it is one of its primary steps that determines what patterns can and cannot be seen from the imagery products in subsequent analyses. Specifically, an adequate segmentation has the power to aggregate pixels into ecological objects that highly realistically represent the overall spectral, spatial and topographical characteristics of individual vegetation patterns and their classes. This invariably improves their distinguishability and thus mappability. However, adequate segmentation of vegetation patterns is unfortunately also one of the most challenging aspects of a mapping approach to get right, and can quickly turn potentially invaluable information into “just pretty pictures”. To a certain extent, this is caused by the lack of comparative testing of different segmentation approaches in vegetation mapping of peatlands and other ecosystems with similar short vegetation structure. Yet, it is also related to the spatial characteristics of peatland vegetation patterns and the technical complexity of using segmentation algorithms in spatial ecology (Hossain & Chen, 2019). Regardless, given the importance of segmentation in mapping vegetation patterns that are at least larger than the raw spatial resolution of drone imagery, it warrants further addressment in this discussion.

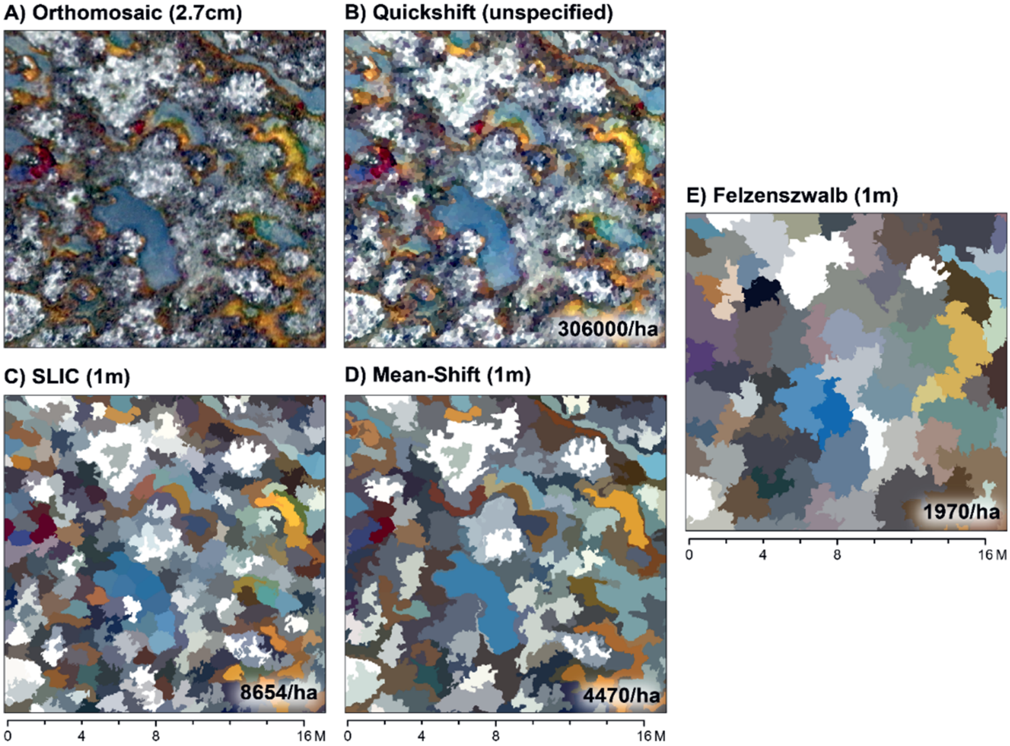

A) Orthomosaic (2.7cm)
B) Quickshift (unspecified)
C) SLIC (1m)
D) Mean-Shift (1m)
E) Felzenszwalb (1m)

Figure 6.2 Overview of the effect of different segmentation algorithms with similar parameterisation on the segmentation accuracy of different peatland vegetation patterns in Carrowbehy bog. Visualised is a snippet of about 17x17m of the same area using imagery with a spatial resolution of 2.7cm (A) retrieved with a DJI Mavic 2 Pro drone. Highlighted in the bottom right corner of each subfigure is the number of segments per hectare resulting from each segmentation. Quickshift is the only algorithm in this list where pre-defined segment sizes cannot be specified.

In theory, it should be sufficient to understand the scale at which ecologically meaningful vegetation patterns exist in a study area, and subsequently conduct a segmentation using a relevant algorithm. However, our findings emphasise that it is extremely difficult to know a priori which segmentation approach best represents vegetation patterns in the field.

Particularly, using segmentation algorithms that create cubic and uniform segments like Mean Shift (Comaniciu & Meer, 2002) and SLIC (Achanta et al., 2012), which we used throughout our research, create segments with relatively cubic and uniform segments. This can be optimal in some vegetation patterns and/or peatlands, but result in poor segmentation for others. Namely, these algorithms cannot capitalise on the unique spatial characteristics of different vegetation pattern classes that are often seen in peatlands (Chapter 2, 3, 4, 5). However, some of the more prevalent segmentation algorithms that can create variably sized and shaped segments like Felzenszwalb and Quickshift (Felzenszwalb & Huttenlocher, 2004; Vedaldi & Soatto, 2008; Figure 6.2B, E) have many technical and unintuitive parameters that all require thorough evaluation to result in segment characteristics that are predictable and representable, especially for segmentation of vegetation patterns. This result in a conundrum because the segmentation algorithms that are theoretically most suitable for vegetation pattern mapping require extensive parameterisation that make accurate and intuitive segmentation only more difficult. Consequently, the most feasible option is often still to conduct a multitude of classifications using various relevant segmentation algorithms and parameters, compare their effects on classification performance and efficiency and then choose the “optimal” combination for the defined study area.

While trial-and-error approaches for segmentation are not problematic, these are inefficient because many segmentations need to be conducted for each study area. Besides, visual interpretation of even the most “optimal” segmented drone imagery in our study still showed inconsistencies, because there was no way to easily assess the full range of possible segmentation parameterisations. To try and overcome the inevitable subjective and time- and labour-intensive nature of such trial-and-error approaches, automated parameterisation for segmentation algorithms has been evaluated by multiple recent studies (e.g. Drăguţ et al., 2010, 2014; Grybas et al., 2017; Johnson et al., 2015; Johnson & Xie, 2011; Nikou et al., 2007; Yang et al., 2015). Further work in this realm is needed to lead to new insights that can help in intuitively estimating the parameters of specific algorithms that are needed for accurate segmentation of peatland vegetation patterns of varying spatial characteristics. In the meantime, segmentation algorithms like Mean Shift and SLIC that can create more predictable segments seem most adequate for most cases. Even so, given the large variability of currently available segmentation approaches, and their key role in driving the accuracy and efficiency of mapping vegetation patterns, studies using segmentation should document their segmentation approach with more detail.

6.1.3.3 Optimising the spectral separability of peatland vegetation patterns

The spectral separability of peatland vegetation patterns was the one of the largest drivers of accuracy in the machine learning models we used for classification (Chapter 2–5). While part of this spectral separability is pre-determined by drone imagery acquisition, pre-processing and segmentation, spectral separability in this thesis was notably affected by two other factors: 1) the process by which raw drone imagery is processed into relevant and meaningful spectral predictor variables for vegetation pattern mapping and 2) plant phenology.

6.1.3.3.1 Computing additional spectral predictor variables

Because we used only drone imagery in the visible spectrum (RGB), considering how to process raw drone imagery optimally into predictor variables was critical. Here, we observed that inclusion of additional spectral predictor variables like the hue-saturation-value colour model values and RGB-based vegetation indices were highly influential in enhancing the overall accuracy of our mapping approach over just raw RGB values. This is because most of the unique vegetation pattern classes in our study area had highly distinct values for some of these additional spectral predictor variables (Chapter 2–5). Even so, we observed occasional misclassifications between spectrally similar vegetation pattern classes, especially when those were occurring at similar locations along the microtopographical gradient (Chapter 2–5).

To address this issue, several studies have highlighted that inclusion of textural features like the commonly used grey-level co-occurrence matrix (GLCM; Haralick et al., 1973) consistently improves classification accuracy of peatland vegetation in such cases (Dissanska et al., 2009; Palace et al., 2018; Räsänen et al., 2020; Räsänen & Virtanen, 2019). Texture represents variation in spectral reflectance in a way that is beneficial in accentuating the canopy structure of a specific vegetation pattern class. Besides, it is particularly suitable in drone-based approaches because individual segments contain up to hundreds of pixels. The difficulty of using texture features in this thesis was that their potential relevance in a mapping approach can be compounded by the window size that is used to compute variation surrounding the pixel of interest, as well as by the accuracy of the segments that are created using specific segmentation algorithms. This requires both knowledge about the vegetation patterns in the field, as well as at least some sensitivity analyses to optimise specific parameters. Nevertheless, given the potential added value of texture features and the relative ease by which they can be calculated from RGB imagery alone, their potential role should be evaluated in future vegetation pattern mapping studies. This way we can systematically increase our understanding of the role of colour texture for improving the mapping accuracy of specific vegetation patterns.

6.1.3.3.2 Plant phenology

We have observed that some of the inconsistencies in our mapping approach were highly likely related to our imagery acquisition in September, which is the end summer and end of the growing season in Irish peatlands. Indeed, while the number of dominant plant species was hardly more than ten in any of the studied peatlands, we saw that some microforms and plant functional types were occasionally misclassified specifically because of flower senescence, peat moss dehydration, dried out carpets of algae in hollows (Chapter 3) and lower water depth in hollows, as this reduced their spectral separability compared to the other vegetation pattern classes (Chapter 2–5). This clearly highlights an important role of plant phenology in the accuracy of vegetation pattern mapping, as was highlighted by several other recent studies in peatlands and other wetlands as well (e.g. Cole et al., 2014; Cruzan et al., 2016; Díaz-Varela et al., 2018; Halabisky et al., 2018; Krankina et al., 2008; Räsänen, Aurela, et al., 2020; Räsänen, Juutinen, et al., 2019; Simpson et al., 2024). Yet, in addition to the temporal aspect of plant phenology, we also saw that phenological states varied spatially along the broader environmental gradients from peatland centre to margin (Chapter 5). This led to inconsistent spectral signatures and variability within some classes in our ground-reference datasets, which resulted in recurring misclassifications between hummocks and lawn and between peat moss and graminoid at the far peatland margins (Chapter 5). This also highlights that model performances from small pilot sites may be inflated if the spectral variability in vegetation patterns increases with the area of the study site (see also 6.1.4).

Although we did not formally analyse the effect of plant phenology on spectral separability in our study, our results highlight potential mapping issues associated with strong spatiotemporal phenological dynamics in peatlands. Classification performance could thus be optimised if images are included from multiple phenological stages, as other studies have shown (e.g. Chen et al., 2017; Chimner et al., 2019; Dudley et al., 2015; Halabisky et al., 2018; Räsänen et al., 2020). However, implementation of multi-temporal drone imagery can be challenging for drone-based mapping approaches because using high spatial resolution imagery requires correspondingly high locational and geometrical positioning (Räsänen & Virtanen, 2019). Besides, peatlands occur along a wide range of latitudes and climatic conditions, and timing of phenological stages therefore differ between broader geographical regions (Park et al., 2021). Phenological states have also started expediting and shifting due to climate change and human disturbances (Antala et al., 2022; Davidson et al., 2021; Juutinen et al., 2017; Mäkiranta et al., 2018), as our observations emphasise.

To accurately and also consistently map peatland vegetation patterns, we still need a great understanding of the spatiotemporal changes in phenology in dominant peatland species over the course of the growing season, and its effect on their spectral separability. To this end, users can take advantage of the flexibility of consumer-grade drones to conduct surveys, map vegetation patterns and evaluate spectral separability and mapping performance in various peatlands during multiple time-periods of the year. It will initially require extensive work to develop spectral libraries with the characteristic signatures of peatland plant species throughout the year for all individual peatlands and peatland types in different geographical regions. However, this will eventually enable us to conduct flights and surveys during time-periods where phenological stages of studied vegetation patterns are most optimal for their identification and differentiation. This will most certainly improve mapping accuracy in future studies, and optimise ground-reference data collection (see also 2.2.4).

6.1.3.4 Predicting below-canopy peat moss cover

Peat moss cover is one of the most important vegetation pattern indicators in peatlands. Therefore, accurate classification of peat moss as either plant functional type, part of a microform, or determinant in habitat characteristics is crucial in many cases when linking vegetation patterns to peatland functions. However, not only was peat moss sometimes misclassified as other vegetation pattern classes (Chapter 2–5), but it was also often missed as we only focused on top-of-canopy vegetation. For instance, in Chapter 5 the 20x20m grid cells with the highest proportions of peat moss in central ecotopes were 45% even though the proportion of peat moss in the same habitat type was often estimated at 90–100% in the field (Fernandez et al., 2014). This mismatch is particularly relevant in subcentral and submarginal ecotopes where peat moss is mostly covered by tall heather and reindeer lichen (Fernandez et al., 2014).

While mapping below-canopy peat moss was beyond the scope of this thesis, it is potentially so relevant in directly classifying habitats (Chapter 5) and functions related to vegetation patterns at all spatial scales that it necessitates inclusion in the general discussion, too. It is also a prime example where inclusion of active camera sensors like LiDAR and radar could become invaluable, as these can penetrate dense canopies and unitedly estimate microtopography and surface soil moisture, which are the most indicative predictor variables of below-canopy peat moss cover. Unfortunately, limitations will still arise when analysing dense and tall peatland vegetation because these diminish the penetration of radar signals (Abdelmajeed & Juszczak, 2024; Millard & Richardson, 2018). Besides, the number of studies focusing on LiDAR and radar for peatland vegetation analysis are limited (Abdelmajeed & Juszczak, 2024), and even more so when it comes to below-canopy vegetation mapping. Radar analyses are also always restricted to satellites because existing drone-based radar systems are typically too heavy for most consumer-grade and research-grade drones. While some existing studies highlight that surface soil moisture can accurately be predicted using satellite radar data (Bechtold et al., 2018; Lees et al., 2021; Millard & Richardson, 2018), they also emphasise that these relationships are inconsistent and negatively affected by fine-scale variation in vegetation and topography. Besides, other studies show that spectral indices from NIR and short-wave infrared are as promising in soil moisture detection in peatlands as radar (Burdun et al., 2020; Meingast et al., 2014; Räsänen et al., 2022). Given the importance of peat moss in driving peatland functions, the potential of these camera sensors in detecting below-canopy peat moss warrants further investigation to ensure that all relevant vegetation patterns for peatland functions are most accurately characterised and are not only limited to top-of-canopy.

6.1.3.5 Refining digital elevation models at peatland scales

While spectral predictor variables resulting from segmenting our drone imagery were often sufficient to distinguish most peatland vegetation patterns, the inclusion of photogrammetry-derived digital elevation models was substantial in advancing the accuracy of our mapping approach. This was especially true in cases where different microforms contained plant functional types with similar spectral signatures. Although we only used the mean relative elevation (or topographic position) of a segment along the microtopographical gradient in most of our research chapters, this predictor variable was near always the most important in classifications of both microforms and plant functional types (Chapter 2–5), especially at the scale of whole peatlands (Chapter 5). These findings align with other recent studies in peatlands who have also highlighted the added value of topography in classifications of vegetation (Harris & Baird, 2019; Kaneko et al., 2024; Li et al., 2024; Moore et al., 2019; Räsänen, Aurela, et al., 2020; Räsänen, Juutinen, et al., 2019, 2020; see also par. 4 of this section).

Nevertheless, the crucial role of topography in our study also meant that inconsistencies and inaccuracies in any of the developed digital terrain models could easily be exacerbated and disproportionally harm our classification models. Regrettably, inconsistencies and inaccuracies in our digital elevation models were commonplace in all research chapters. This was probably caused by limitations in the photogrammetry software, which use ground point filtering methods that are not tailored to ecosystems like peatlands where the surface is almost fully vegetated (Y. Berger Barnett, personal communication, 21 May 2024). Therefore, without adaptations to the ground-point filtering in the photogrammetry software, which was outside the scope of this thesis, any developed digital terrain models practically resembled the vegetation canopy in all but the lowest vegetation pattern classes like peat moss (Y. Berger Barnett, personal communication, 21 May 2024). Canopy height models could therefore not be used in classifications even though these are potentially valuable in discriminating between microforms and plant functional types with similar reflectance but contrasting canopy height and structure (see also Chapter 5.4.1.3). It has to be said that these “false” digital terrain models do not have to be problematic for their use as a predictor variable for mapping peatland vegetation patterns, especially when vegetation cover is homogeneous over all microforms. Namely, assuming that our digital terrain models were in fact surface models reflecting the top of the canopy, it seemed like the relative topographical differences among microforms and plant functional types were still well represented. Possibly, variability in topographic position between microforms and plant functional types was even amplified in our study because peat moss was the only vegetation pattern class that was often filtered as ‘ground’ in the photogrammetry software.

Some of the largest difficulties we faced regarding accurate use of a digital terrain model in our studies was to accommodate for the convex and sloping elevational gradient from peatland centre to margin (Chapter 4, 5). In this thesis, both detrending through higher order polynomial functions (Chapter 2, 3) and moving window averaging (Chapter 4, 5) improved classification performance notably but failed to remove all inconsistencies in the landscape. One could try to address this issue by computing topographic position with multiple window sizes like was done by Räsänen et al. (2019) and Räsänen et al. (2020).

However, this still remains difficult to implement in areas where the peatland surfaces deviate strongly from the ordinary peatland microtopographical gradient. This was often the case in peatlands with complex topography like Derrinea and at the peatland margins in our study area where artificial landscape features often exist due to degradation and/or restoration (see also 5.4.2.4). Computing topographic position is a requirement in classification approaches that aim to use microtopography on the scale of whole peatlands. For this reason, but also because microtopography has such a crucial influence on classification performance of plant functional types, microforms and potentially habitats, there is large need to expand on the generic moving-window averaging approach that was used in this thesis. Developing methods that are adapted to peatlands and variable peatland surfaces will hopefully ensure that both macro- and microtopography are accurately represented in all peatlands regardless of topographical complexity, eco-hydrological integrity and presence of artificial landscape features. This will invariably improve mapping accuracy of all plant functional types, microforms and habitats.

Lastly, we only used the topographic position of vegetation patterns along the microtopographical gradient as an input predictor variable in classification models in our mapping approach. While this already resulted in large increases in mapping accuracy for microforms and plant functional types (Chapter 2–5), the use of additional derivative elevation predictor variables is of high added value to include in future studies to distinguishing between specific vegetation patterns in specific peatlands. This is particularly relevant because vegetation patterns are so tightly linked to the availability of water and nutrients, which in turn is driven by peatland macro and microtopography. Besides, derivative elevation predictor variables can simply be computed from the available photogrammetry products of consumer-grade drone imagery, and are therefore highly advantageous from the perspective of mapping efficiency. In fact, a recent study by Kaneko et al. (2024) found that solely using 23 topographical variables derived from a digital surface model were adequate for distinguishing between four vegetation types in Japanese peatlands, in between our number for microforms and plant functional types. Besides, Räsänen et al. (2019) and Räsänen et al. (2020) found that topographic position at multiple spatial scales, topographic wetness and slope were among the most important predictor variables in classification of plant functional types as well as in predicting their leaf area index and biomass in peatlands in Northern Finland. Lastly, Li et al. (2024) found that vegetation greenness was strongly linked to the extent, distribution and proximity to open water pools in topographic depressions in a peatland in Tibet. The macro-topography of whole peatlands could also be used in classification of habitats because it drives broader water level, nutrient supply and drainage (Schouten, 2002; van der Schaaf, 2002). Moreover, its concentric and convex morphology is often consistently predictable across most peatlands around the world (Cobb et al., 2024).

6.1.4 Development of ground-reference datasets

Accurate and efficient development of ground-reference datasets was among the most important yet difficult aspects of the mapping approach in this thesis (Chapter 2–5). In fact, ground-reference datasets fully determine what kind of spectral, spatial and topographical information about vegetation pattern classes is fed into and out of the classification models. In this way, mapping accuracy can as much be driven by the quality and ecological relevance of the predictor variables as by the accuracy and representativeness of the ground-reference datasets. Nevertheless, few to no studies that mapped peatland vegetation patterns critically evaluated the accuracy and representativeness of their ground-reference datasets. This is possibly because the sensitivity of machine learning classifiers to the size and distribution of ground-reference datasets is not a subject that has been thoroughly investigated (Belgiu & Drăguţ, 2016; Millard & Richardson, 2015), especially not in peatlands.

6.1.4.1 Optimal size of ground-reference datasets

The optimal size and distribution of ground-reference samples remains highly disputed. For instance, several recent studies that analysed the important of ground-reference dataset size in classification performance of machine learning models stated that ground-reference datasets should always be as large as possible (Colditz, 2015; Millard & Richardson, 2015). Initially, we therefore used extremely high sample sizes of up to six thousand samples per hectare (Chapter 2), even though this was tremendously time-consuming and strenuous. However, after investigating the role of ground-reference sample size more thoroughly in our own study area (Chapter 3), we found consistently high classification accuracies for both microforms and plant functional types when using a total ground-reference dataset of “only” 250 samples at areas of 1ha (Chapter 3–5). Besides, ground-reference datasets of 500 samples were adequate both at small scales of only one hectare (Chapter 3–4), and at spatial scales of whole peatlands up to 124ha (Chapter 5).

These results show that what constitutes an “optimal” ground-reference dataset size depends highly on the heterogeneity of the vegetation patterns within the study area in combination with their distinguishability and separability. It is plausible that when mapping increasingly larger peatland areas, initial expansion of ground-reference datasets will improve mapping accuracy because new vegetation pattern classes are incorporated in the expanded study area that may need categorisation and that can influence the distinguishability and separability of already existing vegetation pattern classes. Besides, overall variability may increase due to factors like spatial differences in phenological states (see 6.1.3.3.2) or variation in spectral reflectance due to sun and shading (see 5.4.2.5) that requires addressing. However, at some upper threshold, new sample additions will cease contributing meaningfully to improved classification performance and can even lead to noise because all variability is already captured by the existing ground-reference dataset. As large as possible should therefore mean increasing a ground-reference sample size until the point where additional samples do not additionally benefit model performance. While minimum sample size thresholds for each unique vegetation pattern class is most likely determined by its variability, our findings show that a ground-reference dataset of 500 samples and a minimum of 100 samples per vegetation class were already adequate to capture the overall variability of at least three microforms and six plant functional types even for peatlands up to 124ha in size. This is in line with a study by Olofsson et al. (2014) on good practices for remote sensing mapping.

6.1.4.2 Allocation and spatial distribution of ground-reference samples

In addition to the absolute size of the ground-reference dataset, allocation of ground-reference samples warrants thoughtful decision-making to ensure development of a robust classification model. To this end, the studies by Colditz (2015) and Millard and Richardson (2015) argued that area-proportional allocation of ground-reference samples results in the best classification performance for machine learning models because vegetation patterns that occupy larger areas require more training samples. While this may certainly be true for areas with relatively balanced class proportions and when overall mapping accuracy is important, Olofsson et al. (2013, 2014) recommend shifting a sampling strategy away from area-proportional allocation by increasing the sample size of less-common classes (but not until equal allocation) to achieve more acceptable accuracies and standard errors for all classes. Yet, one should take care that manually placed samples are also distributed adequately throughout the study area.

We found that sample allocation was especially crucial in our study, among other reasons because we used the proportions of less-common but highly indicative vegetation patterns like open water and peat moss to classify peatland habitats (Chapter 5). Besides, this thesis strove to map vegetation patterns in a way that could most accurately represent variability in their functions. This required that all vegetation patterns be classified accurately because functions often differ notably among microforms and plant functional types (see also 1.3.4). In our study area, which contained degraded peatlands, area-proportional allocation would have resulted in severe underrepresentation of less-common vegetation pattern classes like hollow, lawn, peat moss and open water that are indicative of wet surface conditions. This would not only limit the overall representativeness of existing samples, but also disproportionally impact their class-specific model performances (Olofsson et al., 2014; Steenvoorden & Limpens, 2023). Especially when this is important, like in Chapter 4, structural skewness towards dominant vegetation patterns can be particularly impactful because sensitivity of the dominant class for misclassifications is reduced compared to less-common classes. This could lead to incorrect judgement on the distinguishability and separability of specific vegetation patterns (but see also 6.2.5).

6.1.4.3 Methods for acquiring ground-reference samples

Potential inconsistencies in development of ground-reference datasets are further compounded by the fact that ground-reference data is often collected in the field. Not only is this strenuous and time-consuming work on itself, but the high centimetre-level spatial resolution of drone imagery also requires capturing of ground-reference data and ground control points with similarly strict requirements for positional accuracy. This can usually only be achieved with costly high-precision global positioning systems with real time kinematic navigation satellite systems, like the Topcon HiPer HR we used in our study with 1–3cm horizontal and vertical positional accuracy. These are costly, and in most cases require cellular data, which means they are not available for some users and in more remote peatlands. We found that other studies shared similar challenges related to strict requirements for positional accuracy (Antala et al., 2022; Palace et al., 2018). Moreover, it is often hard to evaluate in the field whether all variation in vegetation patterns has been captured adequately. While field-visits and field-surveys are an indispensable component of drone-based remote sensing for identification, categorisation and validation of vegetation pattern classes, it is potentially too time consuming and labour intensive to be used as the sole method for ground-reference dataset development, especially in larger and hard to reach areas. Therefore, ground-reference dataset development could subsequently be conducted using the constructed imagery products (Chapter 3–5). Here, both field surveys and smaller area imagery of higher spatial resolutions could then be used as a reference for validation of imagery-based ground-reference sampling if vegetation patterns are otherwise hard to identify (Räsänen, Elsakov, et al., 2019; Räsänen, Juutinen, et al., 2019; Räsänen & Virtanen, 2019). This requires expertise about the dominant vegetation that can be found in a specific study area, as well as practice in how to identify these from drone imagery products. While this takes time, and initially requires multiple experts to validate ground-reference samples in a variety of peatlands, it may lead to much more efficient mapping approaches.

6.1.5 Estimating uncertainty in mapping accuracy

6.1.5.1 Quantifying mapping uncertainty in vegetation class areas

Variability in mapped areas resulting from misclassifications could have cascading effects when linking vegetation patterns to functions such as carbon fluxes (Olofsson et al., 2013), or when using vegetation pattern classifications from one hierarchical spatial scale as a predictor variable for another (Chapter 5). For these reasons, we require statistically robust and transparent approaches for assessing mapping accuracy, estimating mapped areas and hereby quantifying uncertainty (Olofsson et al., 2014). Particularly, estimating the area of a specific vegetation pattern class in any developed map by purely summing pixels assigned to that vegetation pattern is a biased procedure which leads to erroneous area estimates because the effect of classification errors between vegetation patterns are ignored (Olofsson et al., 2020). Besides, assuming that misclassifications between vegetation patterns offset each other in final mapped areas is possible but highly unlikely, especially when different vegetation patterns within a peatland have highly imbalanced cover (Stehman, 2005). While there are currently many remote sensing classification methods available that take uncertainty into account (Rocchini et al., 2013), we decided to use stratified estimation as our preferred approach (Chapter 3, 4, see Olofsson et al. (2013). We did this particularly because stratified estimates can easily be coupled to common performance metrics resulting from machine learning classifications like Random Forest and Support Vector Machine we employed during our studies. We indeed found that uncertainty in mapped areas were often larger than would be expected based on pixel counting (see also 3.3.2 and 4.2.6). Given these discrepancies, we show it is crucial to make more consistent use of the information obtained from accuracy assessments and at least quantify mapping uncertainty.

6.1.5.2 Ensuring robustness through validation datasets and performance metrics

Especially when developing maps at larger spatial scales, validating the performance of a classification model from sample data to the broader landscape is critical to ensure its robustness and applicability. This invariably requires statistically valid metrics to evaluate such accuracy statements (Olofsson et al., 2014). Machine learning classifiers like Random Forest often have built-in mechanisms to reduce overfitting on training data, such as bagging and feature randomness. However, it is often not corrected to say that this built-in validation method provides unbiased performance of Random Forest models. In fact, out-of-bag score tends to be biased especially with smaller sample sizes, considerable number of predictor variables and equal sample size for classes (Janitza & Hornung, 2018). Therefore, computing performance metrics on a separate validation dataset (or sometimes called test dataset and vice versa) with the same size as the test dataset adds another layer of assurance that model performance is robust (Chapter 4, 5). We suggest that studies mapping vegetation patterns always use validation datasets to help determine whether their models can deal with the complexities and variations of vegetation patterns in the broader peatland landscape.

Moreover, we found that model performance and thus broader mapping accuracy was often heavily influenced by the performance metric used for model evaluation. Particularly, different metrics highlighted distinct aspects of model performance that can lead to contrasting interpretations of a model’s effectiveness in mapping vegetation patterns depending on the classification goal. For instance, simple accuracy would be entirely misleading in our study because vegetation pattern classes (and thus the ground-reference dataset is if it largely-area proportional, see 6.1.4) is imbalanced. We instead computed F1-scores in all cases because it provides a more robust and nuanced evaluation of model performance for all vegetation pattern classes. Still, F1-score might not be the best performance metric in cases where either precision or recall is more costly or impactful. Yet, our study serves to emphasise the importance of critically selecting performance metrics that align with the specific mapping objectives of a study, as well as the vegetation characteristics of the study area and ground-reference dataset.

6.1.5.3 Developing soft-classifications for vegetation pattern mapping

One of the drawbacks of our mapping approach is that it is based on so-called hard classifications, where pre-defined, discrete vegetation classes are unambiguously assigned to segments based on our input predictor variables. While this led to very crisp vegetation pattern maps that are easy to read, this categorical representation is often not in line with the nature’s gradual transitions (Feilhauer et al., 2021; Rocchini, 2014), which is also true in peatlands (Räsänen et al., 2019). Hard classifications can therefore cause problems with vegetation pattern class categorisation and subsequent mapping accuracy. Besides, it is arguable whether the crisp maps that were developed in this thesis serve the application needs of vegetation maps like their functions sufficiently (de Klerk et al., 2018; Rapinel et al., 2018). An alternative to better represent the gradual transitions often found in peatlands is through fuzzy- or soft-classifications. This type of mapping could quantify the uncertainty in developed vegetation pattern maps by predicting the probability that a segment belongs to a specific vegetation pattern class through iterative classification, assuming that they can belong to one or multiple classes (Rocchini, 2010).

Within the mapping approach from this thesis, soft-classifications could already be achieved by using the performance metrics from our cross-validation approach (Chapter 2–5). However, this assumes singular vegetation pattern class labels in the ground-reference datasets, which is not always the optimal way of categorising vegetation. While soft-classifications were beyond the scope of this thesis, they are potentially valuable in achieving more accurate maps of vegetation patterns. Particularly, not only are they ecologically more realistic than crisp vegetation patterns (Räsänen et al., 2019), but they allow quantification of uncertainty in a spatially explicit way. This adds information beyond the spatially unresolved performance metrics that normally result from machine learning classifications (Khatami et al., 2017). In practice, this leads to more detailed understanding of the “fuzzy” character of the peatland landscape, and can help clarify where and in which specific cases hard-classifications may fail. Hereby soft-classifications may result in better sampling strategies, more thorough development of predictor variables and more critical use of the output from machine learning classifications (Zlinszky & Kania, 2016). Because some form of soft-classifications can already be returned from machine learning models with cross-validation approaches, a future opportunity would be to investigate and validate their potential role in complementing hard-classification approaches and improving the mapping methodology.

6.1.6 Upscaling vegetation pattern mapping

6.1.6.1 An upper limit for drone-based vegetation pattern mapping

Based on the results in this thesis, drone-based mapping approaches seem superior over aerial and satellite approaches when mapping vegetation patterns on the peatland-scale. However, the upper boundary of the peatland-scale and thus the scale by which drone imagery analyses could still be considered the most accurate and efficient approach is uncertain. Still, when using the most optimal flight and image processing parameters and ground-reference dataset development methodology from this thesis, it can reach extents of up to 1000ha per day. This is a feasible preliminary “limit” for the peatland-scale because we flew an area of 175ha at 120m flight altitude using only two batteries and a flight time of 40 minutes, even while our DJI Mavic 2 Pro drone has a large sensor compared to other consumer-grade drones. For instance, the DJI Phantom 3 would perform this same flight in 27 minutes, suggesting that areas of 1000ha can theoretically be flown within 1.5 hours of solar noon on the same day. Besides, using spatial resolutions of 0.25m (the minimum spatial resolution requirement from Chapter 4), orthomosaics and digital elevation models for areas of 1000ha can be created with data sizes of “only” 470MB. The same data size would already be reached at surveyed areas of 12ha using raw spatial resolutions. These adjustments to the mapping approach improve pre-processing efficiency and data volumes in a way that facilitates processing times and computational requirements that stay within realistic boundaries for analysis on personal computers. This makes drone-based mapping approach much more accessible and applicable both in peatlands as well as other ecosystems with similar short vegetation structure like moorlands, heathlands and tundra.

6.1.6.2 Assessing the spatial transferability of mapping approaches on the peatland-scale

Upscaling of drone-based mapping approaches initially starts with spatial transferability on the peatland-scale. This way we can ensure that the spectral characteristics of drone imagery and thus the ground-reference datasets that are used in model development to classify and predict vegetation patterns are comparable at least between peatlands of the same type. However, with exception to the spatial transferability analysis for habitat classification (Chapter 5), all of the vegetation pattern maps that were developed in this thesis were peatland-specific. This means that drone imagery was acquired on unique days, development of ground-reference datasets was tailored to imagery of singular peatlands and classifications were also performed only on corresponding peatlands. While most flight and image processing parameters in our research chapters were as uniform as possible, we already highlight multiple factors that influenced the spectral characteristics of the imagery and the ground-reference datasets that were used in model development. These include vegetation composition, plant phenology, weather conditions and sensor characteristics. Hence, caution must already be exercised in assuming the transferability of classification models among the peatlands in our study area.

Understanding what is needed to standardise the spectral reflectance characteristics of imagery datasets between similar peatlands could significantly improve mapping accuracy by better facilitating model comparison and potential model integration, and improve mapping efficiency by taking away part of future ground-reference development (see also 6.1.3.2.2). Collecting drone imagery at the same time-periods and under the same weather conditions were already partially addressed (see 5.4.2.5). Besides, we already aimed to minimise the effect of sun and shading by computing spectral indices that normalise reflectance values, although we did not statistically assess its potential ameliorating effect on reducing spectral variability in areas that were affected by sun and shading. Thus, further research is needed to assess the standardising role of pre-processing steps like radiometric calibration, colour corrections with reference datasets and computing spectral indices that normalise reflectance values.

If large-scale habitats are classified using previously mapped fine-scale vegetation patterns like plant functional types and microforms (Chapter 5), spatial transferability also relates to standardisation of the vegetation proportions that characterise a specific habitat. However, the results of Chapter 5 highlighted that the proportions of remotely sensed vegetation patterns often differed notably from those measured in the field (see also 5.4.3), and also differed between the peatlands in the study area. This means that our habitat mapping approach is currently not spatially transferable because only peatland-specific ground-reference data results in accurate classifications. We suggest several ways to improve the spatial transferability of habitat mapping in section 5.4.3.

6.1.6.3 The potential role of hybrid remote sensing mapping approaches

Upscaling beyond the peatland-scale will require methods that combine the advantages of drones (i.e. high spatiotemporal resolution, photogrammetry and flexible use) with those of satellite remote sensing (i.e. consistent regional and global coverage, wide range of available sensors and no mobilisation requirements; see also **Error! Reference source not found.**). In fact, several recent peatland studies have found that these so-called nested or hybrid drone-aerial and drone-satellite approaches result in better classifications and predictions of vegetation patterns or vegetation attributes (e.g. biomass, greenness, and moisture) than those using imagery from only one type of remote sensing platform (Bhatnagar et al., 2021; Carless et al., 2019; Connolly et al., 2007; Räsänen et al., 2014; Räsänen & Virtanen, 2019; Villoslada et al., 2024). Besides, a pilot experiment that was conducted for this thesis also highlighted that Landsat-9 and Worldview-2 hold exciting potential for predicting the cover of plant functional types and microforms in the studied peatlands based on their drone-derived maps. However, this manuscript was not finished in time for this thesis. In these studies, drones were used to train, test, validate and calibrate coarser spatial resolution aerial and/or satellite imagery (Bhatnagar et al., 2021; Riihimäki et al., 2019; Sjögersten et al., 2023; Villoslada et al., 2024). Still, freely available satellite imagery hardly has a spatial resolution higher than 10m. This means that achieving a sufficiently large ground-reference dataset for accurate and robust model development with a hybrid drone-satellite approach still requires extensively mapped areas. The drone-based mapping approach from this thesis could therefore be extremely valuable for future development of hybrid mapping approaches.

Nevertheless, while hybrid approaches are certainly very promising to upscale vegetation pattern mapping beyond the peatland-scale, such methods are still an indirect way of characterising vegetation patterns on the ground. Namely, the most ideal circumstance would be to directly map vegetation patterns so that their structure and spatial organisation can also be assessed. This requires satellite imagery with submeter spatial resolutions (Räsänen & Virtanen, 2019; Steenvoorden & Limpens, 2023). There are satellites that can satisfy these requirements, such as with commercial satellite imagery from Maxar (Geo-Eye, Worldview, and Quickbird) and Airbus (Pléiades Neo). However, this imagery is often exclusively available on request, costly and requires orders with large areas and minimum widths that may not align with study area sizes and configurations (Figure 1.5). This not only leads to low spatiotemporal coverage compared to freely available Earth observation satellites, but also to low accessibility for general users in spatial ecology.

Consequently, while high spatial resolution satellites hold great potential for directly mapping vegetation patterns on regional and global scales, these are currently not the most efficient option over hybrid approaches for mapping vegetation patterns in most cases.

Hybrid drone-satellite mapping approaches and even large-scale satellite mapping approaches for peatland vegetation patterns are currently scarce, and development of novel approaches is needed to elucidate their potential for upscaling. However, the challenge of hybrid vegetation pattern mapping is that their accuracy is dependent both on the accuracy of the satellite imagery as well as that of the drone-derived maps that are used as ground-reference. Still, it can cautiously be assumed that satellite imagery is corrected for and acquired in a systematic matter. For this reason, most developments for improving hybrid drone-satellite approaches can most likely be achieved by optimising the accuracy and robustness of large-scale drone-derived vegetation pattern maps. The insights from this general discussion can be a valuable starting point from which future studies can further develop, evaluate and optimise both drone-based and hybrid drone-satellite approaches in a variety of peatlands and peatland types, regardless of their spatial complexity and eco-hydrological integrity.

6.2 From form to functions: towards global monitoring of peatland ecosystem services

The final objective of this thesis was to advance the development of accurate, efficient and standardised monitoring workflows for assessing the spatiotemporal dynamics of peatland vegetation patterns and the functions and services they represent. Consequently, we focused on mapping plant functional types, microforms and habitats because these are already three common hierarchical spatial scales when translating peatland vegetation patterns (form) to functions (see also 1.3.4). Admittedly, however, peatlands worldwide vary so much in their characteristics that mapping and monitoring these vegetation patterns and associated functions with a single approach like in this thesis is practically impossible. Yet, there is still need for spatially transferable monitoring approaches of peatland ecosystem services at least within regions with similar peatlands and peatland types so that we can better synthesise and compare peatland protection efforts across countries and regions (Andersen et al., 2017; Minasny et al., 2023; Reed et al., 2022). For these reasons, we already addressed several challenges for large-scale drone-based mapping that transcend the boundary of individual peatlands, peatland types and even the peatland ecosystem itself (see also section 6.1). We also give recommendations for future drone studies that may already improve the accuracy and efficiency of mapping plant functional types, microforms and habitats in a variety of peatlands ranging in vegetation pattern complexity and eco-hydrological integrity, and may aid in mapping of other hierarchical spatial scales (Table 6.1).

Still, the intricate relationship between the hierarchical spatial scale of vegetation patterns, the functions that can be linked to them, and the accuracy and efficiency by which they can be mapped has large implications on how drone-based mapping approaches are designed. This complexity is compounded by the primary focus on ecosystem services in peatland monitoring, which ideally requires mapping approaches that most accurately link form to function. Therefore, trade-offs may arise depending on the peatland functions under evaluation. However, there is also a general need to make mapping approaches as efficient as possible to ensure broad applicability. To this end, I believe we first and foremost require more knowledge about the requirements for most optimally mapping specific peatland functions and the services they represent in a variety of peatlands and peatland types.

6.2.1 Data, resolution and processing requirements for mapping vegetation patterns as ecological indicators

Several recent drone studies in peatlands and other similar ecosystems have already started linking vegetation patterns to functions. For instance, some studies predicted carbon fluxes in peatlands based on maps of microforms (Ivanov et al., 2021; Kelly et al., 2021; Lehmann et al., 2016), plant functional types (Sjögersten et al., 2023) and individual plant species (Lehmann et al., 2016). Others mapped belowground carbon stocks in peatlands based on vegetation height, plant species richness, plant communities and plant biomass (Lopatin et al., 2019). Some more focused on mapping plant biomass through plant functional types (Räsänen, Juutinen, et al., 2020; Villoslada et al., 2024), while others linked biomass directly to canopy height (Cunliffe et al., 2020; Fraser et al., 2016). Studies also directly related spectral indices that link with plant foliar water content to water table depth (Kalacska et al., 2018; Lendzioch et al., 2021), or by extrapolating the topography of open water pools (Rahman et al., 2017). There have also been studies that accurately relate the extent and distribution of peatland habitats to water table depth and peatland-wide carbon fluxes (e.g. Regan et al., 2020; Swenson et al., 2019), even though they relied on existing maps instead of developing them within their respective studies.

The findings from these studies indeed highlight the possibility of monitoring peatland functions through vegetation patterns. However, many of these studies also emphasise misclassifications in the vegetation pattern mapping procedure as a potentially critical issue for upscaling peatland functions. Yet, all studies represented a large variety in all aspects of their mapping approaches and the way their functions were estimated. For instance, even the studies from Ivanov et al. (2021), Kelly et al. (2021) and Lehmann et al. (2016) that focused specifically on predicting carbon fluxes from peatland microforms all used completely different flight altitudes (100m vs 50m vs 30m respectively), sensors (RGB vs RGB/NIR/Thermal vs RGB+NIR), weather conditions (cloudy vs sunny vs partially cloudy), spatial scales (120ha vs 1.3ha vs 1.8ha), conceptualisations of microform classes (three classes vs two classes vs five classes), classification methods (Maximum Likelihood Classification vs Random Forest vs n/a) and mapping units (pixel-based vs pixel-based vs object-based), among other mapping aspects. Consequently, these factors make it extremely hard to compare which aspects of the mapping approach contributed most meaningfully to prediction accuracy and efficiency of the carbon fluxes in the various peatlands within these studies, and what data, resolution and processing parameters are minimally required for an adequate map of peatland carbon fluxes, among other functions.

Because of the currently relatively indiscriminate use of drone-based remote sensing in peatlands, optimal methods for linking vegetation pattern maps to biogeochemical cycles like carbon fluxes are still uncertain. Probably, the distribution of plant functional types or microforms is the desired hierarchical spatial scale, since these are the main ecological indicators of contrasting rates of carbon accumulation and carbon decomposition in peatlands (Bubier et al., 1993; Couwenberg et al., 2011b; Loisel & Yu, 2013b; Lunt et al., 2019; Riutta et al., 2007; Strack, Waddington, et al., 2006; Waddington & Roulet, 1996). Besides, studies show that carbon fluxes in heterogeneous landscapes can be severely overestimated or underestimated if spatial resolutions of employed imagery products are much coarser than the spatial scale of the vegetation patterns under investigation (e.g. Assmann et al., 2020; Becker et al., 2008; Lehmann et al., 2016; Räsänen et al., 2021; Siewert & Olofsson, 2020). However, some studies show that carbon fluxes could be generalised to the level of habitats functions (Regan et al., 2020; Swenson et al., 2019).

In either case, the results from thesis highlight that monitoring of carbon fluxes could then be carried out at scales of whole peatlands with consumer-grade drones and with only imagery in the visible spectrum and topography derived from photogrammetry. We also show that monitoring at this hierarchical spatial scale can be used as an indicator of drying surface conditions (Chapter 2) and habitat extent and structure (Chapter 5). Conversely, if the objective is to perform a detailed survey of all plant biodiversity, or dynamics of specific plant species, a mapping approach needs to be developed and adapted to account for small, rare, below-canopy and/or unique plant species. Such assessments potentially require much more spectral and spatial detail than mapping carbon fluxes (Simpson et al., 2024), which could invariably affect the upscaling potential of a plant biodiversity mapping approach. Meanwhile, when mapping peatland habitat characteristics or other larger landscape features like open water pools, it may be sufficient to only use coarse spatial resolution imagery. This could mean that transitioning from drone to satellite platforms is most efficient.

All in all, the data, resolution and processing requirements for mapping specific peatland vegetation patterns and their functions highly depend on each other. Particularly, to create accurate and detailed maps of functions we require initial data and knowledge about the scales at which peatland functions operate (see also 6.2.2), but obtaining this data on relevant scales often requires accurate and efficient mapping approaches to begin with. Notwithstanding, drone technology is continuously advancing towards standardisation for science practices and our knowledge about the potential role of drone-based mapping for monitoring vegetation patterns and their associated functions is continuously increasing. Consequently, where previously it may have been sufficient for studies to solely explore the role of drones in monitoring peatland functions, it is critical that the drone-based mapping studies of today are conducted more cautiously and rigorously as they provide the baseline for future studies. It is presently inadequate to solely document and present the mapping approach used, especially if the aim is to develop standardised workflows for drone-based remote sensing. Rather, novel drone studies should consistently and comparatively evaluate the added value of specific aspects of a mapping approach on accuracy and efficiency in multiple peatlands and ideally even peatland types within the same study. Only then can we create the more concrete guidelines on data, resolution and processing requirements for drone-based mapping that will significantly advance monitoring of peatland ecosystem services globally. To this end, the sensitivity analyses from Chapter 3–5 could be expanded to assess their robustness in other peatland types, and the recommendations from section 6.1 could already be used a means to evaluate the added value of specific mapping aspects on the accuracy and efficiency for monitoring specific peatland functions.

6.2.2 Standardising the classification system of peatland vegetation patterns

The current scarcity of standardised and broadly applicable drone-based monitoring approaches for peatland ecosystem services is at least partially affected by its technical novelty and resulting knowledge gaps in mapping accuracy and efficiency. However, advancements in this field may also be limited from a “classification” perspective, as it is not fully clear which conceptualisations and hierarchical spatial scale of detail are the most optimal ecological indicators to map specific peatland functions using remote sensing. This in turn obstructs development of guidelines on the requirements for mapping vegetation patterns and their classes as well.

For instance, the EU Habitats Directive distinguishes a total of thirteen broad habitat types for all peatlands in Europe, among which Blanket bogs (code: 7130), Active raised bogs (code: 7110), and Degraded raised bogs still capable of regeneration (code: 7120) are most applicable for raised bogs and blanket bogs in this thesis. Even so, we have seen that multiple subdivisions of the EU-defined habitat types are used for monitoring even within only the Irish raised bogs in our study area. These ecotopes show not only have notably different vegetation patterns (Fernandez et al., 2014), but also specifically contrasting functions (Regan et al., 2020; Swenson et al., 2019) compared to their broader EU-defined habitat type. Moreover, within singular ecotopes are even more subdivisions of different vegetation complexes, all of which consist of different configurations of microforms and plant functional types with arguably contrasting functions related to their spatial patterning (Fernandez et al., 2014, see also 1.3.4). Besides, we found in Chapter 5 that the proportions of plant functional types and microforms that correspond to a specific ecotope can differ notably between similar peatlands of the same type if its definition and vegetation characteristics for remotely sensed mapping is not considered meticulously compared to field-based mapping.

Discretization of vegetation patterns is needed in some ways to allow for mapping using drone-based approaches and when using machine learning classifications. Still, oversimplification of the complex nature of peatland vegetation patterns may lead to bias in peatland functions like carbon fluxes and therefore must be scrutinised. For example, Moore et al. (2019) found that categorising peatland microtopography into the classic hummock-hollow framework led to bias in carbon fluxes compared to using more subtle microtopographical classes. Besides, Becker et al. (2008) similarly found that generalisations of microforms in a mapping study using increasingly lower spatial resolution imagery led to overestimation of carbon-dioxide fluxes by 5% and underestimation of methane fluxes of 6% at a spatial scale of about 1.5ha. Lehmann et al. (2016) even noted 70% lower total methane fluxes from a microform classification compared to a more detailed species-level classification. On larger hierarchical spatial scales, Kou et al. (2022) also found that aggregation of peatland land cover types resulted in bias in regional methane fluxes. These studies exemplify the difficulty in standardisation of peatland vegetation pattern classes in ways that can most accurately, consistently and robustly be linked to their related functions. Therefore, they rightfully argue for critical and quantitative assessment in categorisation or classification of vegetation patterns.

Given the predominant focus on ecosystem services in peatlands, potential answers to these so-called classification questions should indeed be driven by most optimally linking peatland form to functions. In fact, one of the first studies to develop a framework for standardising the measuring and reporting of peatland functions was conducted by Reed et al. (2022). They put forward an agreed collection of measurable variables or ‘target domains’ to achieve climate, hydrological and biodiversity objectives. Here, fine-scale vegetation patterns and habitats were included as high priority target domains, while several other agreed target domains could likely be derived from these vegetation patterns. Although this study emphasised only ‘what’ to measure rather than exactly ‘how’ to measure or report it, approaches like these are critical to converge data collection efforts towards a more standardised outcome. The specific target domains or ecological indicators resulting from this study can now be used as a starting point from which to evaluate which levels of detail are required to most optimally classify their related climate, hydrological and biodiversity functions. Such information can then be used to further guide and optimise drone-based mapping efforts, which in turn will result in more comprehensive insights into peatland functions on increasingly larger spatial scales. This iterative process will unquestionably advance global monitoring of peatland ecosystem services.

6.3 Concluding remarks

This thesis provides clear evidence that accessible consumer-grade drone-based mapping approaches can hold a central role in monitoring peatland functions through their vegetation patterns. This could ultimately lead to more effective peatland protection. However, peatlands remain complex and diverse ecosystems, and we show that aiming to map them adequately warrants highly critical consideration of all aspects of a mapping approach. In fact, haphazard use of remote sensing analyses may not only transform potentially invaluable information into “just pretty pictures”. Incorrect maps of vegetation patterns can also have cascading consequences when they are applied in subsequent mapping efforts, or if their role as ecological indicator for peatland functions and services are applied in matters like investments, restoration evaluation, conflict resolution, and modelling.

Given recent and expected developments in drone technology, I argue we should put more effort into developing, evaluating and optimising drone-based and hybrid drone-satellite mapping approaches that are specifically designed to test their accuracy and efficiency for monitoring vegetation patterns and their associated functions in a variety of peatlands and peatland types. This is what will ultimately determine their applicability in the field. The tremendous variety in peatland characteristics worldwide make mapping their vegetation patterns with a single approach practically impossible. Yet, we should still develop unified processes wherever possible so the peatland community can converge towards the same accurate, efficient and standardised approaches for the collection, management, analysis, reporting and re-use of data. The results from this thesis provide novel and comprehensive insights into the multiple requirements for accurate and efficient vegetation pattern mapping as ecological indicators on which future studies can build to further develop, evaluate and optimise both drone-based and hybrid drone-satellite mapping approaches. I am certain this will slowly but steadily bring the goal of assessing the spatiotemporal dynamics of peatland functions and their services all over the globe ever closer.

Table 6.1 Summary workflow of this thesis highlighting recommendations and opportunities based that can be used as guidelines for future drone studies aimed at mapping vegetation patterns as ecological indicators on the peatland-scale. Presented on the right side of each recommendation or opportunity is either a gear (⚙) or a globe (🌍) to highlight whether it is a mapping aspect that focuses respectively on optimisation of drone-based mapping, monitoring of functions or both.

Drone imagery acquisition (Chapter 6.1.1)

Recommendations

1. Conduct drone surveys at 120m flight altitude if the pixel size of the imagery remains under the size of the vegetation pattern under investigation ⚙
2. Conduct additional drone surveys at lower flight altitudes for ground-referencing and validating vegetation patterns in the field ⚙
3. Use forward- and side-overlap of 75–60% to develop at least visually accurate orthomosaics and digital elevation models. Only use at least 80–80% forward overlap in small study areas ⚙

Opportunities

1. Evaluate flight altitude requirements for mapping plant species in addition to microforms, plant functional types and habitats 🌍
2. Quantitatively ascertain image overlap requirements for most optimal digital elevation models in different peatland types ⚙ 🌍

The value of additional camera sensors (Chapter 6.1.2)

Recommendations

1. Use consumer-grade drones with imagery in the visible spectrum and photogrammetry-derived digital terrain models are adequate to retrieve accurate classifications of most vegetation patterns ⚙ 🌍

Opportunities

1. Include near-infrared imagery in future vegetation pattern mapping approaches whenever possible to improve spectral separability of crucial vegetation pattern classes like peat moss and open water 🌍
2. Quantitatively evaluate the value of additional camera sensors for mapping specific vegetation patterns through comparative testing ⚙ 🌍

Table 6.1 (continued)

Processing drone imagery and deriving predictor variables (Chapter 6.1.3)		
Recommendations		
1	Compute hue-saturation-value colour model values and vegetation indices combining two or more bands to improve spectral separability of classes when using imagery in the visible spectrum	🌍
2	Resample imagery to a spatial resolution that matches the hierarchical spatial scale of interest to improve efficiency without compromising on accuracy	⚙
3	Segment imagery to create more ecologically relevant objects than pixels and to improve efficiency	⚙ 🌍
4	Compute topographic position index irrespective of the absolute accuracy of the terrain model to retrieve the microtopographical gradient of a whole peatland	🌍
Opportunities		
1	Ascertain more optimal spectral windows for drone surveys due the strong spatiotemporal phenological dynamics of peatland vegetation	🌍
2	Investigate the added value of colour texture variables in distinguishing between spectrally similar classes	🌍
3	Develop methods to predict below-canopy peat moss cover to minimise potential effects of peat moss omissions	🌍
4	Improve segmentation algorithms and parameterisation for use in spatial ecology through sensitivity analyses	⚙ 🌍
5	Enhance ground point filtration to improve accuracy of digital terrain models and facilitate development of canopy height models	⚙ 🌍
6	Develop and refine detrending methods that can characterise microtopographical position index in complex topographical situations	🌍
7	Develop predictor variables to distinguish between artificial and natural landscape features.	⚙ 🌍
8	Investigate the added value of derivative topographical variables	⚙ 🌍

Table continues on the next page

Table 6.1 (continued)

Development of ground-reference datasets (Chapter 6.1.4)		
Recommendations		
1	Allocate at least 500 ground-reference samples and a minimum of 100 samples per vegetation pattern class	⚙ 🌍
2	Use combined random and targeted sampling to ensure representative overall mapping accuracy for common and uncommon classes	⚙ 🌍
3	Develop ground-reference datasets using the imagery products directly while using field measurements and higher spatial resolution drone imagery for validation to improve efficiency	⚙ 🌍
Opportunities		
1	Statistically assess the effect of ground-reference dataset size, distribution and independence on mapping accuracy and efficiency	⚙ 🌍
2	Accommodate for internal heterogeneity within vegetation pattern classes in the ground-reference dataset	⚙ 🌍
Estimating uncertainty in mapping accuracy (Chapter 6.1.5)		
Recommendations		
1	Compute F1-scores in addition to accuracy to achieve more nuanced performance evaluation for imbalanced classes within ground-reference datasets	⚙ 🌍
2	Utilise uncertainty metrics like stratified estimation to compute confidence intervals for accuracy and area estimates	⚙ 🌍
3	Evaluate model performance using a cross-validation approach to ensure robustness with various subsets ground-reference samples	⚙ 🌍
4	Employ validation datasets in model development to assess generalisability from sample data	⚙ 🌍
Opportunities		
1	Investigate the potential of soft-classifications in complementing hard-classifications and quantifying spatial uncertainty	⚙ 🌍
2	Evaluate the applicability of other uncertainty measures for evaluation of model performance	🌍

Table 6.1 (continued)

Upscaling vegetation pattern mapping (Chapter 6.1.6)

Recommendations

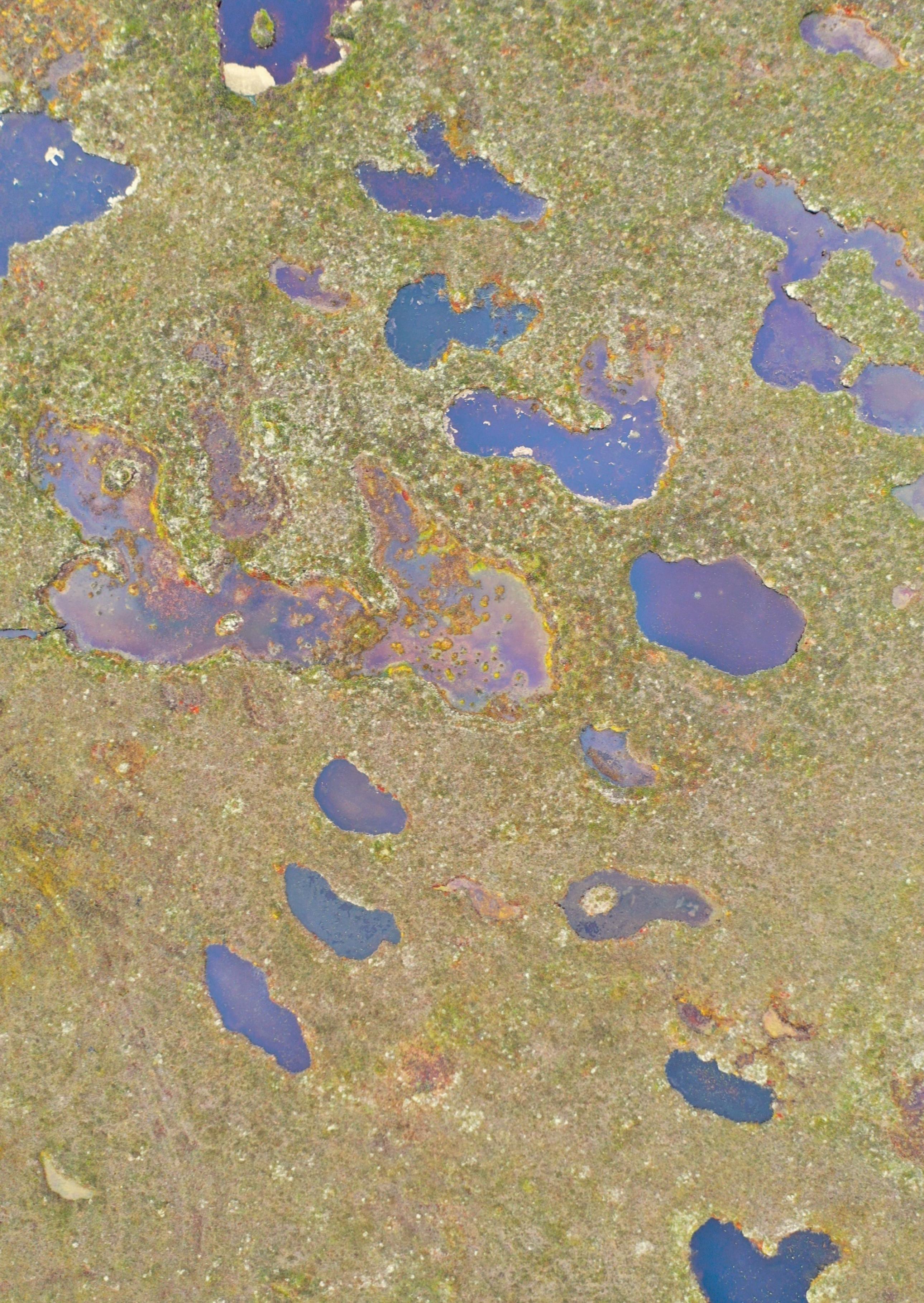
① Using the most optimal flight and image processing parameters from this thesis, drone-based mapping can be carried out up until the peatland-scale (until about 1000ha) ⚙

② Development of hybrid drone-satellite approaches requires drone-based mapping of at least a few hundred hectares to create adequate ground-reference datasets ⚙

Opportunities

① Assess approaches to improve spatial transferability of drone-based mapping between peatlands like radiometric calibration, colour corrections with reference datasets, and normalising spectral indices ⚙

② Develop hybrid drone-satellite approaches to evaluate upscaling potential beyond the peatland-scale ⚙



Chapter 7

References

References

Abdelmajeed, A. Y. A., & Juszczak, R. (2024). Challenges and Limitations of Remote Sensing Applications in Northern Peatlands: Present and Future Prospects. In *Remote Sensing* (Vol. 16, Issue 3). https://doi.org/10.3390/rs16030591

Achanta, R., Shaji, A., Smith, K., Lucchi, A., Fua, P., & Süsstrunk, S. (2012). SLIC superpixels compared to state-of-the-art superpixel methods. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *34*(11). https://doi.org/10.1109/TPAMI.2012.120

Adão, T., Hruška, J., Pádua, L., Bessa, J., Peres, E., Morais, R., & Sousa, J. J. (2017). Hyperspectral imaging: A review on UAV-based sensors, data processing and applications for agriculture and forestry. *Remote Sensing*, *9*(11). https://doi.org/10.3390/rs9111110

Aerts, R., Verhoeven, J. T. A., & Whigham, D. F. (1999). Plant-mediated controls on nutrient cycling in temperate fens and bogs. *Ecology*, *80*(7), 2170–2181. https://doi.org/10.1890/0012-9658(1999)080[2170:PMCONC]2.0.CO;2

Andersen, R., Farrell, C., Graf, M., Muller, F., Calvar, E., Frankard, P., Caporn, S., & Anderson, P. (2017). An overview of the progress and challenges of peatland restoration in Western Europe. In *Restoration Ecology* (Vol. 25, Issue 2). https://doi.org/10.1111/rec.12415

Anderson, K., & Gaston, K. J. (2013). Lightweight unmanned aerial vehicles will revolutionize spatial ecology. In *Frontiers in Ecology and the Environment* (Vol. 11, Issue 3). https://doi.org/10.1890/120150

Andrus, R. E., Wagner, D. J., & Titus, J. E. (1983). Vertical zonation of Sphagnum mosses along hummock-hollow gradients. *Canadian Journal of Botany*, *61*(12), 3128–3139. https://doi.org/10.1139/b83-352

Antala, M., Juszczak, R., van der Tol, C., & Rastogi, A. (2022). Impact of climate change-induced alterations in peatland vegetation phenology and composition on carbon balance. In *Science of the Total Environment* (Vol. 827). https://doi.org/10.1016/j.scitotenv.2022.154294

Arens, M. (2017). *The effect of spatial organization of peatland patterns on the hydrology*. Wageningen University & Research.

Arroyo-Mora, J. P., Kalacska, M., Soffer, R., Ifimov, G., Leblanc, G., Schaaf, E. S., & Lucanus, O. (2018). Evaluation of phenospectral dynamics with Sentinel-2A using a bottom-up approach in a northern ombrotrophic peatland. *Remote Sensing of Environment*, *216*. https://doi.org/10.1016/j.rse.2018.07.021

Assiri, M., Sartori, A., Persichetti, A., Miele, C., Faelga, R. A., Blount, T., & Silvestri, S. (2023). Leaf area index and aboveground biomass estimation of an alpine peatland with a UAV multi-sensor approach. *GIScience and Remote Sensing*, *60*(1). https://doi.org/10.1080/15481603.2023.2270791

Assmann, J. J., Kerby, J. T., Cunliffe, A. M., & Myers-Smith, I. H. (2019). Vegetation monitoring using multispectral sensors — best practices and lessons learned from high latitudes. *Journal of Unmanned Vehicle Systems*, *7*(1). https://doi.org/10.1139/juvs-2018-0018

Assmann, J. J., Myers-Smith, I. H., Kerby, J. T., Cunliffe, A. M., & Daskalova, G. N. (2020). Drone data reveal heterogeneity in tundra greenness and phenology not captured by satellites. *Environmental Research Letters*, *15*(12). https://doi.org/10.1088/1748-9326/abbf7d

Bain, C. G., Bonn, A., Stoneman, R., Chapman, S., Coupar, A., Evans, M., Gearey, B., Howat, M., Joosten, H., Keenleyside, C., Labadz, J., Lindsay, R., Littlewood, N., Lunt, P., Miller, C. J., Moxey, A., Orr, H., Reed, M., Smith, P., … Worrall, F. (2011). IUCN UK Commission of Inquiry on Peatlands. In *IUCN UK Peatland Programme*. https://doi.org/ISBN 978-0-9570572-1-0

Baird, A. J., Milner, A. M., Blundell, A., Swindles, G. T., & Morris, P. J. (2016). Microform-scale variations in peatland permeability and their ecohydrological implications. *Journal of Ecology*, *104*(2). https://doi.org/10.1111/1365-2745.12530

Bechtold, M., Schlaffer, S., Tiemeyer, B., & De Lannoy, G. (2018). Inferring water table depth dynamics from ENVISAT-ASAR C-band backscatter over a range of peatlands from deeply-drained to natural conditions. *Remote Sensing*, *10*(4). https://doi.org/10.3390/rs10040536

Becker, T., Kutzbach, L., Forbrich, I., Schneider, J., Jager, D., Thees, B., & Wilmking, M. (2008). Do we miss the hot spots? - The use of very high resolution aerial photographs to quantify carbon fluxes in peatlands. *Biogeosciences*, *5*(5). https://doi.org/10.5194/bg-5-1387-2008

Behnamian, A., Millard, K., Banks, S. N., White, L., Richardson, M., & Pasher, J. (2017). A Systematic Approach for Variable Selection with Random Forests: Achieving Stable Variable Importance Values. *IEEE Geoscience and Remote Sensing Letters*, *14*(11). https://doi.org/10.1109/LGRS.2017.2745049

Belgiu, M., & Drăguţ, L. (2016). Random forest in remote sensing: A review of applications and future directions. In *ISPRS Journal of Photogrammetry and Remote Sensing* (Vol. 114). https://doi.org/10.1016/j.isprsjprs.2016.01.011

Belyea, L. R. (2013). Nonlinear Dynamics of Peatlands and Potential Feedbacks on the Climate System. In *Carbon Cycling in Northern Peatlands* (pp. 5–18). https://doi.org/10.1029/2008GM000829

Belyea, L. R., & Baird, A. J. (2006). Beyond “the limits to peat bog growth”: Cross-scale feedback in peatland development. *Ecological Monographs*, *76*(3), 299–322. https://doi.org/10.1890/0012-9615(2006)076[0299:BTLTPB]2.0.CO;2

Belyea, L. R., & Clymo, R. S. (2001). Feedback control of the rate of peat formation. *Proceedings of the Royal Society of London. Series B: Biological Sciences*, *268*(1473), 1315–1321. https://doi.org/10.1098/rspb.2001.1665

Belyea, L. R., & Malmer, N. (2004). Carbon sequestration in peatland: patterns and mechanisms of response to climate change. *Global Change Biology*, *10*(7), 1043–1052. https://doi.org/10.1111/j.1529-8817.2003.00783.x

Benscoter, B. W., Greenacre, D., & Turetsky, M. R. (2015). Wildfire as a key determinant of peatland microtopography. *Canadian Journal of Forest Research*, *45*(8), 1132–1136. https://doi.org/10.1139/cjfr-2015-0028

Benscoter, B. W., & Wieder, R. K. (2003). Variability in organic matter lost by combustion in a boreal bog during the 2001 Chisholm fire. *Canadian Journal of Forest Research*, *33*(12). https://doi.org/10.1139/x03-162

Berendse, F., Van Breemen, N., Rydin, Ha., Buttler, A., Heijmans, M., Hoosbeek, M. R., Lee, J. A., Mitchell, E., Saarinen, T., Vasander, H., & Wallen, B. (2001). Raised atmospheric CO2 levels and increased N deposition cause shifts in plant species composition and production in Sphagnum bogs. *Global Change Biology*, *7*(5), 591–598. https://doi.org/10.1046/j.1365-2486.2001.00433.x

Bertacchi, A., Giannini, V., Di Franco, C., & Silvestri, N. (2019). Using unmanned aerial vehicles for vegetation mapping and identification of botanical species in wetlands. *Landscape and Ecological Engineering*, *15*(2). https://doi.org/10.1007/s11355-018-00368-1

Beyer, F., Jurasinski, G., Couwenberg, J., & Grenzdörffer, G. (2019). Multisensor data to derive peatland vegetation communities using a fixed-wing unmanned aerial vehicle. *International Journal of Remote Sensing*, *40*(24), 9103–9125. https://doi.org/10.1080/01431161.2019.1580825

Bhatnagar, S., Gill, L., & Ghosh, B. (2020). Drone image segmentation using machine and deep learning for mapping raised bog vegetation communities. *Remote Sensing*, *12*(16). https://doi.org/10.3390/RS12162602

Bhatnagar, S., Gill, L., Regan, S., Naughton, O., Johnston, P., Waldren, S., & Ghosh, B. (2020). MAPPING VEGETATION COMMUNITIES INSIDE WETLANDS USING SENTINEL-2 IMAGERY IN IRELAND. *International Journal of Applied Earth Observation and Geoinformation*, *88*. https://doi.org/10.1016/j.jag.2020.102083

Bhatnagar, S., Gill, L., Regan, S., Waldren, S., & Ghosh, B. (2021). A nested drone-satellite approach to monitoring the ecological conditions of wetlands. *ISPRS Journal of Photogrammetry and Remote Sensing*, *174*. https://doi.org/10.1016/j.isprsjprs.2021.01.012

Blaschke, T., Hay, G. J., Kelly, M., Lang, S., Hofmann, P., Addink, E., Queiroz Feitosa, R., van der Meer, F., van der Werff, H., van Coillie, F., & Tiede, D. (2014). Geographic Object-Based Image Analysis – Towards a new paradigm. *ISPRS Journal of Photogrammetry and Remote Sensing*, *87*, 180–191. https://doi.org/10.1016/j.isprsjprs.2013.09.014

Blier-Langdeau, A., Guêné-Nanchen, M., Hugron, S., & Rochefort, L. (2021). The resistance and short-term resilience of a restored extracted peatland ecosystems post-fire: an opportunistic study after a wildfire. *Restoration Ecology*. https://doi.org/10.1111/rec.13545

Blockeel, T. L., Bell, N. E., Hill, M. O., Hodgetts, N. G., Long, D. G., Pilkington, S. L., & Rothero, G. P. (2021). A new checklist of the bryophytes of Britain and Ireland, 2020. *Journal of Bryology*, *43*(1). https://doi.org/10.1080/03736687.2020.1860866

Bonn, A., Allott, T., Evans, M., Joosten, H., & Stoneman, R. (2016). Peatland Restoration and Ecosystem Services. In A. Bonn, T. Allott, M. Evans, H. Joosten, & R. Stoneman (Eds.), *Peatland Restoration and Ecosystem Services: Science, Policy and Practice*. Cambridge University Press. https://doi.org/10.1017/CBO9781139177788

Bonn, A., Reed, M. S., Evans, C. D., Joosten, H., Bain, C., Farmer, J., Emmer, I., Couwenberg, J., Moxey, A., Artz, R., Tanneberger, F., von Unger, M., Smyth, M. A., & Birnie, D. (2014). Investing in nature: Developing ecosystem service markets for peatland restoration. *Ecosystem Services*, *9*. https://doi.org/10.1016/j.ecoser.2014.06.011

Bosch, M. (2019). PyLandStats: An open-source Pythonic library to compute landscape metrics. *PLoS ONE*, *14*(12). https://doi.org/10.1371/journal.pone.0225734

Bragazza, L., Bardgett, R. D., Mitchell, E. A. D., & Buttler, A. (2015). Linking soil microbial communities to vascular plant abundance along a climate gradient. *New Phytologist*, *205*(3), 1175–1182. https://doi.org/10.1111/nph.13116

Bragazza, L., Buttler, A., Robroek, B. J. M., Albrecht, R., Zaccone, C., Jassey, V. E. J., & Signarbieux, C. (2016). Persistent high temperature and low precipitation reduce peat carbon accumulation. *Global Change Biology*, *22*(12), 4114–4123. https://doi.org/10.1111/gcb.13319

Bragazza, L., Parisod, J., Buttler, A., & Bardgett, R. D. (2013). Biogeochemical plant–soil microbe feedback in response to climate warming in peatlands. *Nature Climate Change*, *3*(3), 273–277. https://doi.org/10.1038/nclimate1781

Branham, J. E., & Strack, M. (2014). Saturated hydraulic conductivity in Sphagnum-dominated peatlands: Do microforms matter? *Hydrological Processes*, *28*(14). https://doi.org/10.1002/hyp.10228

Breeuwer, A., Robroek, B. J. M., Limpens, J., Heijmans, M. M. P. D., Schouten, M. G. C., & Berendse, F. (2009). Decreased summer water table depth affects peatland vegetation. *Basic and Applied Ecology*, *10*(4), 330–339. https://doi.org/10.1016/j.baae.2008.05.005

Breiman, L. (2001). Random forests. *Machine Learning*, *45*, 5–32. https://doi.org/10.1023/A:1010933404324

Bu, Z.-J., Zheng, X. X., Rydin, H., Moore, T., & Ma, J. (2013). Facilitation vs. competition: Does interspecific interaction affect drought responses in Sphagnum? *Basic and Applied Ecology*. https://doi.org/10.1016/j.baae.2013.08.002

Bubier, J., Costello, A., Moore, T. R., Roulet, N. T., & Savage, K. (1993). Microtopography and methane flux in boreal peatlands, northern Ontario, Canada. *Canadian Journal of Botany*, *71*(8). https://doi.org/10.1139/b93-122

Bubier, J. L., Moore, T. R., & Bledzki, L. A. (2007). Effects of nutrient addition on vegetation and carbon cycling in an ombrotrophic bog. *Global Change Biology*, *13*(6), 1168–1186. https://doi.org/10.1111/j.1365-2486.2007.01346.x

Bubier, J. L., Rock, B. N., & Crill, P. M. (1997). Spectral reflectance measurements of boreal wetland and forest mosses. *Journal of Geophysical Research Atmospheres*, *102*(24). https://doi.org/10.1029/97jd02316

Buck, H. J., & Palumbo-Compton, A. (2022). Soil carbon sequestration as a climate strategy: what do farmers think? *Biogeochemistry*, *161*(1). https://doi.org/10.1007/s10533-022-00948-2

Bullock, C. H., & Collier, M. (2011). When the public good conflicts with an apparent preference for unsustainable behaviour. *Ecological Economics*, *70*(5). https://doi.org/10.1016/j.ecolecon.2010.12.013

Burdun, I., Bechtold, M., Sagris, V., Komisarenko, V., Lannoy, G. De, & Mander, Ü. (2020). A comparison of three trapezoid models using optical and thermal satellite imagery for water table depth monitoring in Estonian Bogs. *Remote Sensing*, *12*(12). https://doi.org/10.3390/rs12121980

Burger, J., & Gowen, A. (2011). Data handling in hyperspectral image analysis. *Chemometrics and Intelligent Laboratory Systems*, *108*(1). https://doi.org/10.1016/j.chemolab.2011.04.001

Byg, A., Martin-Ortega, J., Glenk, K., & Novo, P. (2017). Conservation in the face of ambivalent public perceptions – The case of peatlands as ‘the good, the bad and the ugly.’ *Biological Conservation*, *206*. https://doi.org/10.1016/j.biocon.2016.12.022

Cao, J., Leng, W., Liu, K., Liu, L., He, Z., & Zhu, Y. (2018). Object-Based mangrove species classification using unmanned aerial vehicle hyperspectral images and digital surface models. *Remote Sensing*, *10*(1). https://doi.org/10.3390/rs10010089

Carless, D., Luscombe, D. J., Gatis, N., Anderson, K., & Brazier, R. E. (2019). Mapping landscape-scale peatland degradation using airborne lidar and multispectral data. *Landscape Ecology*, *34*(6). https://doi.org/10.1007/s10980-019-00844-5

Chapman, S., Buttler, A., Francez, A. J., Laggoun-Défarge, F., Vasander, H., Schloter, M., Combe, J., Grosvernier, P., Harms, H., Epron, D., Gilbert, D., & Mitchell, E. (2003). Exploitation of northern peatlands and biodiversity maintenance: A conflict between economy and ecology. In *Frontiers in Ecology and the Environment* (Vol. 1, Issue 10). https://doi.org/10.1890/1540-9295(2003)001[0525:EONPAB]2.0.CO;2

Chen, B., Chen, L., Lu, M., & Xu, B. (2017). Wetland mapping by fusing fine spatial and hyperspectral resolution images. *Ecological Modelling*, *353*. https://doi.org/10.1016/j.ecolmodel.2017.01.004

Chimner, R. A., Bourgeau-Chavez, L., Grelik, S., Hribljan, J. A., Clarke, A. M. P., Polk, M. H., Lilleskov, E. A., & Fuentealba, B. (2019). Mapping Mountain Peatlands and Wet Meadows Using Multi-Date, Multi-Sensor Remote Sensing in the Cordillera Blanca, Peru. *Wetlands*, *39*(5). https://doi.org/10.1007/s13157-019-01134-1

Cobb, A. R., Dommain, R., Yeap, K., Hannan, C., Dadap, N. C., Bookhagen, B., Glaser, P. H., & Harvey, C. F. (2024). A unified explanation for the morphology of raised peatlands. *Nature*, *625*(7993). https://doi.org/10.1038/s41586-023-06807-w

Cohen, J., Screen, J. A., Furtado, J. C., Barlow, M., Whittleston, D., Coumou, D., Francis, J., Dethloff, K., Entekhabi, D., Overland, J., & Jones, J. (2014). Recent Arctic amplification and extreme mid-latitude weather. *Nature Geoscience*, *7*(9), 627–637. https://doi.org/10.1038/ngeo2234

Colditz, R. R. (2015). An evaluation of different training sample allocation schemes for discrete and continuous land cover classification using decision tree-based algorithms. *Remote Sensing*, *7*(8). https://doi.org/10.3390/rs70809655

Cole, B., McMorrow, J., & Evans, M. (2014). Spectral monitoring of moorland plant phenology to identify a temporal window for hyperspectral remote sensing of peatland. *ISPRS Journal of Photogrammetry and Remote Sensing*, *90*. https://doi.org/10.1016/j.isprsjprs.2014.01.010

Comaniciu, D., & Meer, P. (2002). Mean shift: A robust approach toward feature space analysis. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *24*(5). https://doi.org/10.1109/34.1000236

Connolly, J. (2018). Mapping land use on Irish peatlands using medium resolution satellite imagery. *Irish Geography*, *51*(2). https://doi.org/10.2014/igj.v51i2.1371

Connolly, J., & Holden, N. M. (2009). Mapping peat soils in Ireland: Updating the derived Irish peat map. *Irish Geography*, *42*(3). https://doi.org/10.1080/00750770903407989

Connolly, J., Holden, N. M., & Ward, S. M. (2007). Mapping Peatlands in Ireland using a Rule-Based Methodology and Digital Data. *Soil Science Society of America Journal*, *71*(2). https://doi.org/10.2136/sssaj2006.0033

Couwenberg, J., Thiele, A., Tanneberger, F., Augustin, J., Bärisch, S., Dubovik, D., Liashchynskaya, N., Michaelis, D., Minke, M., Skuratovich, A., & Joosten, H. (2011a). Assessing greenhouse gas emissions from peatlands using vegetation as a proxy. *Hydrobiologia*, *674*(1), 67–89. https://doi.org/10.1007/s10750-011-0729-x

Couwenberg, J., Thiele, A., Tanneberger, F., Augustin, J., Bärisch, S., Dubovik, D., Liashchynskaya, N., Michaelis, D., Minke, M., Skuratovich, A., & Joosten, H. (2011b). Assessing greenhouse gas emissions from peatlands using vegetation as a proxy. *Hydrobiologia*, *674*(1), 67–89. https://doi.org/10.1007/s10750-011-0729-x

Crowley, W., Smith, G. F., Mackin, F., Regan, S., Fernandez Valverde, F., & Eakin, M. (2021). RECOVERY OF THE VEGETATION OF A CUTOVER RAISED BOG IN IRELAND FOLLOWING REWETTING MEASURES. *Biology and Environment*, *121B*(2). https://doi.org/10.3318/BIOE.2021.09

Crutsinger, G. M., Short, J., & Sollenberger, R. (2016). The future of uavs in ecology: An insider perspective from the silicon valley drone industry. In *Journal of Unmanned Vehicle Systems* (Vol. 4, Issue 3). https://doi.org/10.1139/juvs-2016-0008

Cruzan, M. B., Weinstein, B. G., Grasty, M. R., Kohrn, B. F., Hendrickson, E. C., Arredondo, T. M., & Thompson, P. G. (2016). Small Unmanned Aerial Vehicles (Micro-Uavs, Drones) in Plant Ecology. *Applications in Plant Sciences*, *4*(9). https://doi.org/10.3732/apps.1600041

Cunliffe, A. M., J Assmann, J., N Daskalova, G., Kerby, J. T., & Myers-Smith, I. H. (2020). Aboveground biomass corresponds strongly with drone-derived canopy height but weakly with greenness (NDVI) in a shrub tundra landscape. *Environmental Research Letters*, *15*(12). https://doi.org/10.1088/1748-9326/aba470

Czapiewski, S. (2022). Assessment of the Applicability of UAV for the Creation of Digital Surface Model of a Small Peatland. *Frontiers in Earth Science*, *10*. https://doi.org/10.3389/feart.2022.834923

Czapiewski, S., & Szumińska, D. (2022). An overview of remote sensing data applications in peatland research based on works from the period 2010–2021. In *Land* (Vol. 11, Issue 1). https://doi.org/10.3390/land11010024

Dalponte, M., Ørka, H. O., Gobakken, T., Gianelle, D., & Næsset, E. (2013). Tree species classification in boreal forests with hyperspectral data. *IEEE Transactions on Geoscience and Remote Sensing*, *51*(5). https://doi.org/10.1109/TGRS.2012.2216272

Davidson, S. J., Goud, E. M., Malhotra, A., Estey, C. O., Korsah, P., & Strack, M. (2021). Linear Disturbances Shift Boreal Peatland Plant Communities Toward Earlier Peak Greenness. *Journal of Geophysical Research: Biogeosciences*, *126*(8). https://doi.org/10.1029/2021JG006403

de Klerk, H. M., Burgess, N. D., & Visser, V. (2018). Probabilistic description of vegetation ecotones using remote sensing. *Ecological Informatics*, *46*. https://doi.org/10.1016/j.ecoinf.2018.06.001

de Roos, S., Turner, D., Lucieer, A., & Bowman, D. M. J. S. (2018). Using digital surface models from UAS imagery of fire damaged sphagnum peatlands for monitoring and hydrological restoration. *Drones*, *2*(4). https://doi.org/10.3390/drones2040045

De Zeeuw, J. W. (1978). Peat and the Dutch Golden Age. The historical meaning of energy-attainability. *AAG Bijdragen*, *21*.

Díaz-Varela, R. A., Calvo Iglesias, S., Cillero Castro, C., & Díaz Varela, E. R. (2018). Sub-metric analisis of vegetation structure in bog-heathland mosaics using very high resolution rpas imagery. *Ecological Indicators*, *89*. https://doi.org/10.1016/j.ecolind.2017.11.068

Dieleman, C. M., Branfireun, B. A., McLaughlin, J. W., & Lindo, Z. (2015). Climate change drives a shift in peatland ecosystem plant community: Implications for ecosystem function and stability. *Global Change Biology*, *21*(1), 388–395. https://doi.org/10.1111/gcb.12643

Dise, N. B. (2009). Peatland response to global change. In *Science* (Vol. 326, Issue 5954). https://doi.org/10.1126/science.1174268

Dissanska, M., Bernier, M., & Payette, S. (2009). Object-based classification of very high resolution panchromatic images for evaluating recent change in the structure of patterned peatlands. *Canadian Journal of Remote Sensing*, *35*(2). https://doi.org/10.5589/m09-002

Dorrepaal, E., Cornelissen, J. H. C., Aerts, R., Wallén, B., & van Logtestijn, R. S. P. (2005). Are growth forms consistent predictors of leaf litter quality and decomposability across peatlands along a latitudinal gradient? *Journal of Ecology*, *93*(4), 817–828. https://doi.org/10.1111/j.1365-2745.2005.01024.x

Drăguţ, L., Csillik, O., Eisank, C., & Tiede, D. (2014). Automated parameterisation for multi-scale image segmentation on multiple layers. *ISPRS Journal of Photogrammetry and Remote Sensing*, *88*. https://doi.org/10.1016/j.isprsjprs.2013.11.018

Drăguţ, L., Tiede, D., & Levick, S. R. (2010). ESP: A tool to estimate scale parameter for multiresolution image segmentation of remotely sensed data. *International Journal of Geographical Information Science*, *24*(6). https://doi.org/10.1080/13658810903174803

Dronova, I. (2015). Object-based image analysis in wetland research: A review. In *Remote Sensing* (Vol. 7, Issue 5). https://doi.org/10.3390/rs70506380

Dronova, I., Gong, P., Clinton, N. E., Wang, L., Fu, W., Qi, S., & Liu, Y. (2012). Landscape analysis of wetland plant functional types: The effects of image segmentation scale, vegetation classes and classification methods. *Remote Sensing of Environment*, *127*. https://doi.org/10.1016/j.rse.2012.09.018

Dronova, I., Kislik, C., Dinh, Z., & Kelly, M. (2021). A review of unoccupied aerial vehicle use in wetland applications: Emerging opportunities in approach, technology, and data. In *Drones* (Vol. 5, Issue 2). https://doi.org/10.3390/drones5020045

Dudley, K. L., Dennison, P. E., Roth, K. L., Roberts, D. A., & Coates, A. R. (2015). A multi-temporal spectral library approach for mapping vegetation species across spatial and temporal phenological gradients. *Remote Sensing of Environment*, *167*. https://doi.org/10.1016/j.rse.2015.05.004

Duffy, J. P., Cunliffe, A. M., DeBell, L., Sandbrook, C., Wich, S. A., Shutler, J. D., Myers-Smith, I. H., Varela, M. R., & Anderson, K. (2018). Location, location, location: considerations when using lightweight drones in challenging environments. *Remote Sensing in Ecology and Conservation*, *4*(1). https://doi.org/10.1002/rse2.58

Eppinga, M. B., de Ruiter, P. C., Wassen, M. J., & Rietkerk, M. (2009). Nutrients and hydrology indicate the driving mechanisms of peatland surface patterning. *American Naturalist*, *173*(6). https://doi.org/10.1086/598487

Eppinga, M. B., Rietkerk, M., Borren, W., Lapshina, E. D., Bleuten, W., & Wassen, M. J. (2008). Regular Surface Patterning of Peatlands: Confronting Theory with Field Data. *Ecosystems*, *11*(4), 520–536. https://doi.org/10.1007/s10021-008-9138-z

Eppinga, M. B., Rietkerk, M., Wassen, M. J., & De Ruiter, P. C. (2009). Linking habitat modification to catastrophic shifts and vegetation patterns in bogs. *Plant Ecology*, *200*(1), 53–68. https://doi.org/10.1007/s11258-007-9309-6

Escobar, D., Belyazid, S., & Manzoni, S. (2022). Back to the Future: Restoring Northern Drained Forested Peatlands for Climate Change Mitigation. In *Frontiers in Environmental Science* (Vol. 10). https://doi.org/10.3389/fenvs.2022.834371

Evans, C. D., Peacock, M., Baird, A. J., Artz, R. R. E., Burden, A., Callaghan, N., Chapman, P. J., Cooper, H. M., Coyle, M., Craig, E., Cumming, A., Dixon, S., Gauci, V., Grayson, R. P., Helfter, C., Heppell, C. M., Holden, J., Jones, D. L., Kaduk, J., … Morrison, R. (2021). Overriding water table control on managed peatland greenhouse gas emissions. *Nature*, *593*(7860). https://doi.org/10.1038/s41586-021-03523-1

Fawcett, D., Panigada, C., Tagliabue, G., Boschetti, M., Celesti, M., Evdokimov, A., Biriukova, K., Colombo, R., Miglietta, F., Rascher, U., & Anderson, K. (2020). Multi-scale evaluation of drone-based multispectral surface reflectance and vegetation indices in operational conditions. *Remote Sensing*, *12*(3). https://doi.org/10.3390/rs12030514

Feilhauer, H., Zlinszky, A., Kania, A., Foody, G. M., Doktor, D., Lausch, A., & Schmidtlein, S. (2021). Let your maps be fuzzy!—Class probabilities and floristic gradients as alternatives to crisp mapping for remote sensing of vegetation. *Remote Sensing in Ecology and Conservation*, *7*(2). https://doi.org/10.1002/rse2.188

Felzenszwalb, P. F., & Huttenlocher, D. P. (2004). Efficient graph-based image segmentation. *International Journal of Computer Vision*, *59*(2). https://doi.org/10.1023/B:VISI.0000022288.19776.77

Fernandez, F., Connolly, K., Crowley, W., Denyer, J., Duff, K., & Smith, G. (2014). *Raised Bog Monitoring and Assessment Survey 2013*. https://www.npws.ie/sites/default/files/publications/pdf/IWM81_0.pdf

Fernandez, F., Crowley, W., & Wilson, S. (2012). *Raised Bog Monitoring Project 2011 - Volume 1: Main Report*.

Fick, S. E., & Hijmans, R. J. (2017). WorldClim 2: new 1-km spatial resolution climate surfaces for global land areas. *International Journal of Climatology*, *37*(12), 4302–4315. https://doi.org/10.1002/joc.5086

Flint, A., & Jennings, B. (2020). Saturated with meaning: peatlands, heritage and folklore. *Time and Mind*, *13*(3). https://doi.org/10.1080/1751696X.2020.1815293

Flood, K., Mahon, M., & McDonagh, J. (2021). Assigning value to cultural ecosystem services: The significance of memory and imagination in the conservation of Irish peatlands. *Ecosystem Services*, *50*. https://doi.org/10.1016/j.ecoser.2021.101326

Fraser, R. H., Olthof, I., Lantz, T. C., & Schmitt, C. (2016). UAV photogrammetry for mapping vegetation in the low-Arctic. *Arctic Science*, *2*(3). https://doi.org/10.1139/as-2016-0008

Frolking, S., Talbot, J., Jones, M. C., Treat, C. C., Kauffman, J. B., Tuittila, E.-S., & Roulet, N. (2011). Peatlands in the Earth's 21st century climate system. *Environmental Reviews*, *19*(NA), 371–396. https://doi.org/10.1139/a11-014

Gadonneix, P., Nadeau, M.-J., Kim, Y. D., Birnbaum, L., Cho, H., Choudhury, A. R., da Costa Carvalho Neto, J., Dauger, J.-M., Meyers, K., Sambo, A., Statham, B. A., Vargas Lieras, J. A., Ward, G., Xinxiong, W., Zatari, T. M., & Frei, C. (2013). *World Energy Resources*.

Gallego-Sala, A. v., Clark, J. M., House, J. I., Orr, H. G., Prentice, I. C., Smith, P., Farewell, T., & Chapman, S. J. (2010). Bioclimatic envelope model of climate change impacts on blanket peatland distribution in Great Britain. *Climate Research*, *45*(1). https://doi.org/10.3354/cr00911

Gallego-Sala, A. V., & Colin Prentice, I. (2013). Blanket peat biome endangered by climate change. *Nature Climate Change*, *3*(2), 152–155. https://doi.org/10.1038/nclimate1672

Gavazov, K., Albrecht, R., Buttler, A., Dorrepaal, E., Garnett, M. H., Gogo, S., Hagedorn, F., Mills, R. T. E., Robroek, B. J. M., & Bragazza, L. (2018). Vascular plant-mediated controls on atmospheric carbon assimilation and peat carbon decomposition under climate change. *Global Change Biology*, *24*(9). https://doi.org/10.1111/gcb.14140

Georganos, S., Grippa, T., Vanhuysse, S., Lennert, M., Shimoni, M., Kalogirou, S., & Wolff, E. (2018). Less is more: optimizing classification performance through feature selection in a very-high-resolution remote sensing object-based urban application. *GIScience and Remote Sensing*, *55*(2). https://doi.org/10.1080/15481603.2017.1408892

Glenk, K., & Martin-Ortega, J. (2018). The economics of peatland restoration. *Journal of Environmental Economics and Policy*, *7*(4). https://doi.org/10.1080/21606544.2018.1434562

Glenk, K., Schaafsma, M., Moxey, A., Martin-Ortega, J., & Hanley, N. (2014). A framework for valuing spatially targeted peatland restoration. *Ecosystem Services*, *9*. https://doi.org/10.1016/j.ecoser.2014.02.008

González, E., Rochefort, L., Boudreau, S., & Poulin, M. (2014). Combining indicator species and key environmental and management factors to predict restoration success of degraded ecosystems. *Ecological Indicators*, *46*. https://doi.org/10.1016/j.ecolind.2014.06.016

Goud, E. M., Moore, T. R., & Roulet, N. T. (2017). Predicting peatland carbon fluxes from non-destructive plant traits. *Functional Ecology*, *31*(9). https://doi.org/10.1111/1365-2435.12891

Granlund, L., Vesakoski, V., Sallinen, A., Kolari, T. H. M., Wolff, F., & Tahvanainen, T. (2021). Recent Lateral Expansion of Sphagnum Bogs Over Central Fen Areas of Boreal Aapa Mire Complexes. *Ecosystems*. https://doi.org/10.1007/s10021-021-00726-5

Grybas, H., Melendy, L., & Congalton, R. G. (2017). A comparison of unsupervised segmentation parameter optimization approaches using moderate- and high-resolution imagery. *GIScience and Remote Sensing*, *54*(4). https://doi.org/10.1080/15481603.2017.1287238

Gunnarsson, U., Malmer, N., & Rydin, H. (2002). Dynamics or constancy in Sphagnum dominated mire ecosystems? A 40-year study. *Ecography*, *25*(6), 685–704. https://doi.org/10.1034/j.1600-0587.2002.250605.x

Günther, A., Barthelmes, A., Huth, V., Joosten, H., Jurasinski, G., Koebsch, F., & Couwenberg, J. (2020). Prompt rewetting of drained peatlands reduces climate warming despite methane emissions. *Nature Communications*, *11*(1). https://doi.org/10.1038/s41467-020-15499-z

Haapalehto, T. O., Vasander, H., Jauhiainen, S., Tahvanainen, T., & Kotiaho, J. S. (2011). The Effects of Peatland Restoration on Water-Table Depth, Elemental Concentrations, and Vegetation: 10 Years of Changes. *Restoration Ecology*, *19*(5), 587–598. https://doi.org/10.1111/j.1526-100X.2010.00704.x

Hájek, T., Ballance, S., Limpens, J., Zijlstra, M., & Verhoeven, J. T. A. (2011). Cell-wall polysaccharides play an important role in decay resistance of Sphagnum and actively depressed decomposition in vitro. *Biogeochemistry*. https://doi.org/10.1007/s10533-010-9444-3

Halabisky, M., Babcock, C., & Moskal, L. M. (2018). Harnessing the temporal dimension to improve object-based image analysis classification of wetlands. *Remote Sensing*, *10*(9). https://doi.org/10.3390/rs10091467

Haralick, R. M., Dinstein, I., & Shanmugam, K. (1973). Textural Features for Image Classification. *IEEE Transactions on Systems, Man and Cybernetics*, *SMC-3*(6). https://doi.org/10.1109/TSMC.1973.4309314

Harris, A., & Baird, A. J. (2019). Microtopographic Drivers of Vegetation Patterning in Blanket Peatlands Recovering from Erosion. *Ecosystems*, *22*(5). https://doi.org/10.1007/s10021-018-0321-6

Harris, A., & Bryant, R. G. (2009a). A multi-scale remote sensing approach for monitoring northern peatland hydrology: Present possibilities and future challenges. *Journal of Environmental Management*, *90*(7). https://doi.org/10.1016/j.jenvman.2007.06.025

Harris, A., & Bryant, R. G. (2009b). Northern peatland vegetation and the carbon cycle: A remote sensing approach. *Geophysical Monograph Series*, *184*. https://doi.org/10.1029/2008GM000818

Harris, A., Charnock, R., & Lucas, R. M. (2015). Hyperspectral remote sensing of peatland floristic gradients. *Remote Sensing of Environment*, *162*. https://doi.org/10.1016/j.rse.2015.01.029

Harris, L. I., Roulet, N. T., & Moore, T. R. (2020). Drainage reduces the resilience of a boreal peatland. *Environmental Research Communications*, *2*(6), 065001. https://doi.org/10.1088/2515-7620/ab9895

He, X., He, K. S., & Hyvönen, J. (2016). Will bryophytes survive in a warming world? *Perspectives in Plant Ecology, Evolution and Systematics*, *19*, 49–60. https://doi.org/10.1016/j.ppees.2016.02.005

Heijmans, M. M. P. D., van der KLnaap, Y. A. M., Holmgren, M., & Limpens, J. (2013). Persistent versus transient tree encroachment of temperate peat bogs: effects of climate warming and drought events. *Global Change Biology*, *19*(7), 2240–2250. https://doi.org/10.1111/gcb.12202

Helbig, M., Waddington, J. M., Alekseychik, P., Amiro, B. D., Aurela, M., Barr, A. G., Black, T. A., Blanken, P. D., Carey, S. K., Chen, J., Chi, J., Desai, A. R., Dunn, A., Euskirchen, E. S., Flanagan, L. B., Forbrich, I., Friborg, T., Grelle, A., Harder, S., … Zyrianov, V. (2020). Increasing contribution of peatlands to boreal evapotranspiration in a warming climate. *Nature Climate Change*, *10*(6), 555–560. https://doi.org/10.1038/s41558-020-0763-7

Hirschler, O., & Osterburg, B. (2022). Peat extraction, trade and use in Europe: a material flow analysis. *Mires and Peat*, *28*. https://doi.org/10.19189/MaP.2021.SNPG.StA.2315

Hobbie, S. E. (1996). Temperature and Plant Species Control Over Litter Decomposition in Alaskan Tundra. *Ecological Monographs*, *66*(4), 503–522. https://doi.org/10.2307/2963492

Holmgren, M., Lin, C.-Y., Murillo, J. E., Nieuwenhuis, A., Penninkhof, J., Sanders, N., van Bart, T., van Veen, H., Vasander, H., Vollebregt, M. E., & Limpens, J. (2015). Positive shrub-tree interactions facilitate woody encroachment in boreal peatlands. *Journal of Ecology*, *103*(1), 58–66. https://doi.org/10.1111/1365-2745.12331

Hossain, M. D., & Chen, D. (2019). Segmentation for Object-Based Image Analysis (OBIA): A review of algorithms and challenges from remote sensing perspective. In *ISPRS Journal of Photogrammetry and Remote Sensing* (Vol. 150). https://doi.org/10.1016/j.isprsjprs.2019.02.009

Huang, Y., Ciais, P., Luo, Y., Zhu, D., Wang, Y., Qiu, C., Goll, D. S., Guenet, B., Makowski, D., de Graaf, I., Leifeld, J., Kwon, M. J., Hu, J., & Qu, L. (2021). Tradeoff of CO2 and CH4 emissions from global peatlands under water-table drawdown. *Nature Climate Change*, *11*(7). https://doi.org/10.1038/s41558-021-01059-w

Ikkala, L., Ronkanen, A. K., Ilmonen, J., Similä, M., Rehell, S., Kumpula, T., Päkkilä, L., Klöve, B., & Marttila, H. (2022). Unmanned Aircraft System (UAS) Structure-From-Motion (SfM) for Monitoring the Changed Flow Paths and Wetness in Minerotrophic Peatland Restoration. *Remote Sensing*, *14*(13). https://doi.org/10.3390/rs14133169

Iljas, T. (2022). *Using Very High Resolution Remotely Piloted Aircraft Imagery to Map Peatland Vegetation Composition and Configuration Patterns within an Elevation Gradient* [Master Thesis]. University of Waterloo.

IPCC. (2023). Summary for Policymakers: Climate Change 2023 Synthesis Report. *Climate Change 2023: Synthesis Report. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*.

Ivanov, D. G., Kotlov, I. P., Minayeva, T. Yu., & Kurbatova, J. A. (2021). Estimation of carbon dioxide fluxes on a ridge-hollow bog complex using a high resolution orthophotoplan. *Nature Conservation Research*, *6*(2). https://doi.org/10.24189/ncr.2021.020

Janitza, S., & Hornung, R. (2018). On the overestimation of random forest's out-of-bag error. *PLoS ONE*, *13*(8). https://doi.org/10.1371/journal.pone.0201904

Jassey, V. E., Chiapusio, G., Binet, P., Buttler, A., Laggoun-Défarge, F., Delarue, F., Bernard, N., Mitchell, E. A., Toussaint, M.-L., Francez, A.-J., & Gilbert, D. (2013). Above- and belowground linkages in Sphagnum peatland: climate warming affects plant-microbial interactions. *Global Change Biology*, *19*(3), 811–823. https://doi.org/10.1111/gcb.12075

Jiang, G., & Wang, W. (2017). Error estimation based on variance analysis of k-fold cross-validation. *Pattern Recognition*, *69*. https://doi.org/10.1016/j.patcog.2017.03.025

Jiang, J., Johansen, K., Tu, Y. H., & McCabe, M. F. (2022). Multi-sensor and multi-platform consistency and interoperability between UAV, Planet CubeSat, Sentinel-2, and Landsat reflectance data. *GIScience and Remote Sensing*, *59*(1). https://doi.org/10.1080/15481603.2022.2083791

Johnson, B. A., Bragais, M., Endo, I., Magcale-Macandog, D. B., & Macandog, P. B. M. (2015). Image segmentation parameter optimization considering within-and between-segment heterogeneity at multiple scale levels: Test case for mapping residential areas using landsat imagery. *ISPRS International Journal of Geo-Information*, *4*(4). https://doi.org/10.3390/ijgi4042292

Johnson, B., & Xie, Z. (2011). Unsupervised image segmentation evaluation and refinement using a multi-scale approach. *ISPRS Journal of Photogrammetry and Remote Sensing*, *66*(4). https://doi.org/10.1016/j.isprsjprs.2011.02.006

Johnson, L. C., & Damman, A. W. H. (1991). Species-Controlled Sphagnum Decay on a South Swedish Raised Bog. *Oikos*, *61*(2). https://doi.org/10.2307/3545341

Johnson, M. G., Granath, G., Tahvanainen, T., Pouliot, R., Stenøien, H. K., Rochefort, L., Rydin, H., & Shaw, A. J. (2015). Evolution of niche preference in Sphagnum peat mosses. *Evolution*, *69*(1). https://doi.org/10.1111/evo.12547

Joosten, H. (2009a). Human Impacts: Farming, Fire, Forestry and Fuel. In *The Wetlands Handbook*. https://doi.org/10.1002/9781444315813.ch30

Joosten, H. (2009b). *The Global Peatland CO2 Picture: Peatland status and drainage related emissions in all the countries of the world*. Wetlands International.

Joosten, H. (2016). Peatlands across the globe. In *Peatland Restoration and Ecosystem Services: Science, Policy and Practice*. https://doi.org/10.1017/CBO9781139177788.003

Joosten, H., & Clarke, D. (2002). Wise Use of Mires and Peatlands. In *International Mire Conservation Group and International Peat Society, Helsinki*.

Juutinen, S., Virtanen, T., Kondratyev, V., Laurila, T., Linkosalmi, M., Mikola, J., Nyman, J., Räsänen, A., Tuovinen, J. P., & Aurela, M. (2017). Spatial variation and seasonal dynamics of leaf-Area index in the arctic tundra-implications for linking ground observations and satellite images. *Environmental Research Letters*, *12*(9). https://doi.org/10.1088/1748-9326/aa7f85

Kalacska, M., Arroyo-Mora, J. P., & Lucanus, O. (2021). Comparing uas lidar and structure-from-motion photogrammetry for peatland mapping and virtual reality (Vr) visualization. *Drones*, *5*(2). https://doi.org/10.3390/drones5020036

Kalacska, M., Arroyo-Mora, J. P., Soffer, R. J., Roulet, N. T., Moore, T. R., Humphreys, E., Leblanc, G., Lucanus, O., & Inamdar, D. (2018). Estimating Peatland water table depth and net ecosystem exchange: A comparison between satellite and airborne imagery. *Remote Sensing*, *10*(5). https://doi.org/10.3390/rs10050687

Kalacska, M., Lucanus, O., Soffer, R. J., Leblanc, G., & Arroyo-Mora, J. P. (2017). *Spectro-spatial relationship between UAV derived high resolution DEM and SWIR hyperspectral data: application to an ombrotrophic peatland*. https://doi.org/10.1117/12.2277874

Kaneko, K., Yokochi, M., Inoue, T., Kato, Y., & Fujita, H. (2024). Topographic conditions as governing factors of mire vegetation types analyzed from drone-based terrain model. *Journal of Vegetation Science*, *35*(1). https://doi.org/10.1111/jvs.13226

Kelly, J., Kljun, N., Eklundh, L., Klemedtsson, L., Liljebladh, B., Olsson, P. O., Weslien, P., & Xie, X. (2021). Modelling and upscaling ecosystem respiration using thermal cameras and UAVs: Application to a peatland during and after a hot drought. *Agricultural and Forest Meteorology*, *300*. https://doi.org/10.1016/j.agrformet.2021.108330

Kelly, L. (1993). *Hydrology, Hydrochemistry and Vegetation of Two Raised Bogs in Co. Offaly* [PhD Thesis]. Trinity College Dublin.

Kettridge, N., Turetsky, M. R., Sherwood, J. H., Thompson, D. K., Miller, C. A., Benscoter, B. W., Flannigan, M. D., Wotton, B. M., & Waddington, J. M. (2015). Moderate drop in water table increases peatland vulnerability to post-fire regime shift. *Scientific Reports*, *5*(1), 8063. https://doi.org/10.1038/srep08063

Khatami, R., Mountrakis, G., & Stehman, S. V. (2017). Mapping per-pixel predicted accuracy of classified remote sensing images. *Remote Sensing of Environment*, *191*. https://doi.org/10.1016/j.rse.2017.01.025

Knoth, C., Klein, B., Prinz, T., & Kleinebecker, T. (2013). Unmanned aerial vehicles as innovative remote sensing platforms for high-resolution infrared imagery to support restoration monitoring in cut-over bogs. *Applied Vegetation Science*, *16*(3), 509–517. https://doi.org/10.1111/avsc.12024

Koebsch, F., Sonnentag, O., Järveoja, J., Peltoniemi, M., Alekseychik, P., Aurela, M., Arslan, A. N., Dinsmore, K., Gianelle, D., Helfter, C., Jackowicz-Korczynski, M., Korrensalo, A., Leith, F., Linkosalmi, M., Lohila, A., Lund, M., Maddison, M., Mammarella, I., Mander, Ü., … Peichl, M. (2020). Refining the role of phenology in regulating gross ecosystem productivity across European peatlands. *Global Change Biology*, *26*(2). https://doi.org/10.1111/gcb.14905

Kolari, T. H. M., Korpelainen, P., Kumpula, T., & Tahvanainen, T. (2021). Accelerated vegetation succession but no hydrological change in a boreal fen during 20 years of recent climate change. *Ecology and Evolution*, *11*(12). https://doi.org/10.1002/ece3.7592

Kolari, T. H. M., Sallinen, A., Wolff, F., Kumpula, T., Tolonen, K., & Tahvanainen, T. (2022). Ongoing Fen–Bog Transition in a Boreal Aapa Mire Inferred from Repeated Field Sampling, Aerial Images, and Landsat Data. *Ecosystems*, *25*(5). https://doi.org/10.1007/s10021-021-00708-7

Kosenius, A.-K., Haltia, E., Horne, P., Kniivilä, M., & Saastamoinen, O. (2013). Value of ecosystem services? Examples and experiences on forests, peatlands, agricultural lands, and freshwaters in Finland. In *PTT raportteja 244* (Issue December).

Kou, D., Virtanen, T., Treat, C. C., Tuovinen, J. P., Räsänen, A., Juutinen, S., Mikola, J., Aurela, M., Heiskanen, L., Heikkilä, M., Weckström, J., Juselius, T., Piilo, S. R., Deng, J., Zhang, Y., Chaudhary, N., Huang, C., Väliranta, M., Biasi, C., … Shurpali, N. J. (2022). Peatland Heterogeneity Impacts on Regional Carbon Flux and Its Radiative Effect Within a Boreal Landscape. *Journal of Geophysical Research: Biogeosciences*, *127*(9). https://doi.org/10.1029/2021JG006774

Krankina, O. N., Pflugmacher, D., Friedl, M., Cohen, W. B., Nelson, P., & Baccini, A. (2008). Meeting the challenge of mapping peatlands with remotely sensed data. *Biogeosciences*, *5*(6). https://doi.org/10.5194/bg-5-1809-2008

Krohn, J., Lozanovska, I., Kuzyakov, Y., Parvin, S., & Dorodnikov, M. (2017). CH4 and CO2 production below two contrasting peatland micro-relief forms: An inhibitor and δ13C study. *Science of the Total Environment*, *586*. https://doi.org/10.1016/j.scitotenv.2017.01.192

Kross, A. S. E., Roulet, N. T., Moore, T. R., Lafleur, P. M., Humphreys, E. R., Seaquist, J. W., Flanagan, L. B., & Aurela, M. (2014). Phenology and its role in carbon dioxide exchange processes in northern peatlands. *Journal of Geophysical Research: Biogeosciences*, *119*(7). https://doi.org/10.1002/2014JG002666

Kursa, M. B., & Rudnicki, W. R. (2010). Feature selection with the boruta package. *Journal of Statistical Software*, *36*(11). https://doi.org/10.18637/jss.v036.i11

Laine, A., Byrne, K. A., Kiely, G., & Tuittila, E.-S. (2007). Patterns in Vegetation and CO2 Dynamics along a Water Level Gradient in a Lowland Blanket Bog. *Ecosystems*, *10*(6), 890–905. https://doi.org/10.1007/s10021-007-9067-2

Laine, A. M., Bubier, J., Riutta, T., Nilsson, M. B., Moore, T. R., Vasander, H., & Tuittila, E. S. (2012). Abundance and composition of plant biomass as potential controls for mire net ecosytem CO 2 exchange. *Botany*, *90*(1). https://doi.org/10.1139/B11-068

Lamentowicz, M., Gałka, M., Marcisz, K., Słowiński, M., Kajukało-Drygalska, K., Dayras, M. D., & Jassey, V. E. J. (2019). Unveiling tipping points in long-term ecological records from Sphagnum -dominated peatlands. *Biology Letters*, *15*(4), 20190043. https://doi.org/10.1098/rsbl.2019.0043

Lang, S. I., Cornelissen, J. H. C., Klahn, T., van Logtestijn, R. S. P., Broekman, R., Schweikert, W., & Aerts, R. (2009). An experimental comparison of chemical traits and litter decomposition rates in a diverse range of subarctic bryophyte, lichen and vascular plant species. *Journal of Ecology*, *97*(5). https://doi.org/10.1111/j.1365-2745.2009.01538.x

Lapen, D. R., Price, J. S., & Gilbert, R. (2005). Modelling two-dimensional steady-state groundwater flow and flow sensitivity to boundary conditions in blanket peat complexes. *Hydrological Processes*, *19*(2). https://doi.org/10.1002/hyp.1507

Larrinaga, A. R., & Brotons, L. (2019). Greenness indices from a low-cost UAV imagery as tools for monitoring post-fire forest recovery. *Drones*, *3*(1). https://doi.org/10.3390/drones3010006

Lees, K. J., Artz, R. R. E., Chandler, D., Aspinall, T., Boulton, C. A., Buxton, J., Cowie, N. R., & Lenton, T. M. (2021). Using remote sensing to assess peatland resilience by estimating soil surface moisture and drought recovery. *Science of the Total Environment*, *761*. https://doi.org/10.1016/j.scitotenv.2020.143312

Lees, K. J., Quaife, T., Artz, R. R. E., Khomik, M., & Clark, J. M. (2018). Potential for using remote sensing to estimate carbon fluxes across northern peatlands – A review. In

Science of the Total Environment (Vol. 615). https://doi.org/10.1016/j.scitotenv.2017.09.103

Lehmann, J., Münchberger, W., Knoth, C., Blodau, C., Nieberding, F., Prinz, T., Pancotto, V., & Kleinebecker, T. (2016). High-Resolution Classification of South Patagonian Peat Bog Microforms Reveals Potential Gaps in Up-Scaled CH4 Fluxes by use of Unmanned Aerial System (UAS) and CIR Imagery. *Remote Sensing*, *8*(3), 173. https://doi.org/10.3390/rs8030173

Lendzioch, T., Langhammer, J., Vlček, L., & Minařík, R. (2021). Mapping the groundwater level and soil moisture of a montane peat bog using uav monitoring and machine learning. *Remote Sensing*, *13*(5). https://doi.org/10.3390/rs13050907

Li, Y., Yu, Z., Wang, M., Li, H., Sun, J., & Wang, S. (2024). Control of local topography and surface patterning on the formation and stability of a slope permafrost peatland at 4800-m elevation on the central Qinghai-Tibetan Plateau. *Ecological Indicators*, *158*. https://doi.org/10.1016/j.ecolind.2023.111475

Limpens, J., Granath, G., Gunnarsson, U., Aerts, R., Bayley, S., Bragazza, L., Bubier, J., Buttler, A., van den Berg, L. J. L., Francez, A.-J., Gerdol, R., Grosvernier, P., Heijmans, M. M. P. D., Hoosbeek, M. R., Hotes, S., Ilomets, M., Leith, I., Mitchell, E. A. D., Moore, T., … Xu, B. (2011). Climatic modifiers of the response to nitrogen deposition in peat-forming Sphagnum mosses: a meta-analysis. *New Phytologist*, *191*(2), 496–507. https://doi.org/10.1111/j.1469-8137.2011.03680.x

Limpens, J., Holmgren, M., Jacobs, C. M. J., Van der Zee, S. E. A. T. M., Karofeld, E., & Berendse, F. (2014). How Does Tree Density Affect Water Loss of Peatlands? A Mesocosm Experiment. *PLoS ONE*, *9*(3), e91748. https://doi.org/10.1371/journal.pone.0091748

Linkosalmi, M., Tuovinen, J.-P., Nevalainen, O., Peltoniemi, M., Taniş, C. M., Arslan, A. N., Rainne, J., Lohila, A., Laurila, T., & Aurela, M. (2022). Tracking vegetation phenology of pristine northern boreal peatlands by combining digital photography with CO_2 flux and remote sensing data. *Biogeosciences*, *19*(19), 4747–4765. https://doi.org/10.5194/bg-19-4747-2022

Lõhmus, A., Remm, L., & Rannap, R. (2015). Just a Ditch in Forest? Reconsidering Draining in the Context of Sustainable Forest Management. *BioScience*, *65*(11). https://doi.org/10.1093/biosci/biv136

Loisel, J., Gallego-Sala, A. v., Amesbury, M. J., Magnan, G., Anshari, G., Beilman, D. W., Benavides, J. C., Blewett, J., Camill, P., Charman, D. J., Chawchai, S., Hedgpeth, A., Kleinen, T., Korhola, A., Large, D., Mansilla, C. A., Müller, J., van Bellen, S., West, J. B., … Wu, J. (2021). Expert assessment of future vulnerability of the global peatland carbon sink. *Nature Climate Change*, *11*(1). https://doi.org/10.1038/s41558-020-00944-0

Loisel, J., & Yu, Z. C. (2013). Surface vegetation patterning controls carbon accumulation in peatlands. *Geophysical Research Letters*, *40*(20), 5508–5513. https://doi.org/10.1002/grl.50744

Loisel, J., Yu, Z. C., Beilman, D. W., Camill, P., Alm, J., Amesbury, M. J., Anderson, D., Andersson, S., Bochicchio, C., Barber, K., Belyea, L. R., Bunbury, J., Chambers, F. M., Charman, D. J., De Vleeschouwer, F., Fiałkiewicz-Kozieł, B., Finkelstein, S. A., Gałka, M., Garneau, M., … Zhou, W. (2014). A database and synthesis of northern peatland soil properties and Holocene carbon and nitrogen accumulation. *Holocene*. https://doi.org/10.1177/0959683614538073

Lopatin, J., Kattenborn, T., Galleguillos, M., Perez-Quezada, J. F., & Schmidtlein, S. (2019). Using aboveground vegetation attributes as proxies for mapping peatland belowground carbon stocks. *Remote Sensing of Environment*, *231*. https://doi.org/10.1016/j.rse.2019.111217

Lovitt, J., Rahman, M. M., & McDermid, G. J. (2017). Assessing the Value of UAV Photogrammetry for Characterizing Terrain in Complex Peatlands. *Remote Sensing*, *9*(7), 715. https://doi.org/10.3390/rs9070715

Lunt, P. H., Fyfe, R. M., & Tappin, A. D. (2019). Role of recent climate change on carbon sequestration in peatland systems. *Science of the Total Environment*, *667*. https://doi.org/10.1016/j.scitotenv.2019.02.239

Ma, L., Zhu, G., Chen, B., Zhang, K., Niu, S., Wang, J., Ciais, P., & Zuo, H. (2022). A globally robust relationship between water table decline, subsidence rate, and carbon release from peatlands. *Communications Earth and Environment*, *3*(1). https://doi.org/10.1038/s43247-022-00590-8

Mackin, F., Barr, A., Rath, P., Eakin, M., Ryan, J., Jeffrey, R., & Valverde, F. F. (2017). *Best practice in raised bog restoration in Ireland*.

https://www.npws.ie/sites/default/files/publications/pdf/IWM99_RB_Restoration_Best Practice Guidance.pdf

Macrae, M. L., Devito, K. J., Strack, M., & Waddington, J. M. (2013). Effect of water table drawdown on peatland nutrient dynamics: Implications for climate change. *Biogeochemistry*, *112*(1–3). https://doi.org/10.1007/s10533-012-9730-3

Mäkiranta, P., Laiho, R., Mehtätalo, L., Straková, P., Sormunen, J., Minkkinen, K., Penttilä, T., Fritze, H., & Tuittila, E. S. (2018). Responses of phenology and biomass production of boreal fens to climate warming under different water-table level regimes. *Global Change Biology*, *24*(3). https://doi.org/10.1111/gcb.13934

Makrickas, E., Manton, M., Angelstam, P., & Grygoruk, M. (2023). Trading wood for water and carbon in peatland forests? Rewetting is worth more than wood production. *Journal of Environmental Management*, *341*. https://doi.org/10.1016/j.jenvman.2023.117952

Malone, S., & O'Connell, C. (2009). Ireland's Peatland Conservation Action Plan 2020 – halting the loss of peatland biodiversity. In *Irish Peatland Conservation Council, Kildare*.

Manfreda, S., McCabe, M. F., Miller, P. E., Lucas, R., Madrigal, V. P., Mallinis, G., Dor, E. Ben, Helman, D., Estes, L., Ciraolo, G., Müllerová, J., Tauro, F., de Lima, M. I., de Lima, J. L. M. P., Maltese, A., Frances, F., Caylor, K., Kohv, M., Perks, M., … Toth, B. (2018). On the use of unmanned aerial systems for environmental monitoring. In *Remote Sensing* (Vol. 10, Issue 4). https://doi.org/10.3390/rs10040641

Mao, R., Zhang, X., Song, C., Wang, X., & Finnegan, P. M. (2018). Plant functional group controls litter decomposition rate and its temperature sensitivity: An incubation experiment on litters from a boreal peatland in northeast China. *Science of The Total Environment*, *626*, 678–683. https://doi.org/10.1016/j.scitotenv.2018.01.162

Martínez-Carricondo, P., Agüera-Vega, F., Carvajal-Ramírez, F., Mesas-Carrascosa, F.-J., García-Ferrer, A., & Pérez-Porras, F.-J. (2018). Assessment of UAV-photogrammetric mapping accuracy based on variation of ground control points. *International Journal of Applied Earth Observation and Geoinformation*, *72*, 1–10. https://doi.org/10.1016/j.jag.2018.05.015

McCarter, C. P. R., & Price, J. S. (2014). Ecohydrology of Sphagnum moss hummocks: mechanisms of capitula water supply and simulated effects of evaporation. *Ecohydrology*, *7*(1), 33–44. https://doi.org/10.1002/eco.1313

McPartland, M. Y., Falkowski, M. J., Reinhardt, J. R., Kane, E. S., Kolka, R., Turetsky, M. R., Douglas, T. A., Anderson, J., Edwards, J. D., Palik, B., & Montgomery, R. A. (2019). Characterizing boreal peatland plant composition and species diversity with hyperspectral remote sensing. *Remote Sensing*, *11*(14). https://doi.org/10.3390/rs11141685

Meingast, K. M., Falkowski, M. J., Kane, E. S., Potvin, L. R., Benscoter, B. W., Smith, A. M. S., Bourgeau-Chavez, L. L., & Miller, M. E. (2014). Spectral detection of near-surface moisture content and water-table position in northern peatland ecosystems. *Remote Sensing of Environment*, *152*. https://doi.org/10.1016/j.rse.2014.07.014

Melton, J. R., Chan, E., Millard, K., Fortier, M., Winton, R. S., Martín-López, J. M., Cadillo-Quiroz, H., Kidd, D., & Verchot, L. V. (2022). A map of global peatland extent created using machine learning (Peat-ML). *Geoscientific Model Development*, *15*(12). https://doi.org/10.5194/gmd-15-4709-2022

Mercer, J. J., & Westbrook, C. J. (2016). Ultrahigh-resolution mapping of peatland microform using ground-based structure from motion with multiview stereo. *Journal of Geophysical Research: Biogeosciences*, *121*(11). https://doi.org/10.1002/2016JG003478

Millard, K., & Richardson, M. (2013). Wetland mapping with LiDAR derivatives, SAR polarimetric decompositions, and LiDAR-SAR fusion using a random forest classifier. *Canadian Journal of Remote Sensing*, *39*(4). https://doi.org/10.5589/m13-038

Millard, K., & Richardson, M. (2015). On the importance of training data sample selection in Random Forest image classification: A case study in peatland ecosystem mapping. *Remote Sensing*, *7*(7). https://doi.org/10.3390/rs70708489

Millard, K., & Richardson, M. (2018). Quantifying the relative contributions of vegetation and soil moisture conditions to polarimetric C-Band SAR response in a temperate peatland. *Remote Sensing of Environment*, *206*. https://doi.org/10.1016/j.rse.2017.12.011

Miller, C. A., Benscoter, B. W., & Turetsky, M. R. (2015). The effect of long-term drying associated with experimental drainage and road construction on vegetation composition and productivity in boreal fens. *Wetlands Ecology and Management*, *23*(5), 845–854. https://doi.org/10.1007/s11273-015-9423-5

Minasny, B., Adetsu, D. V., Aitkenhead, M., Artz, R. R. E., Baggaley, N., Barthelmes, A., Beucher, A., Caron, J., Conchedda, G., Connolly, J., Deragon, R., Evans, C., Fadnes, K., Fiantis, D., Gagkas, Z., Gilet, L., Gimona, A., Glatzel, S., Greve, M. H., … Zak, D. (2023). Mapping and monitoring peatland conditions from global to field scale. *Biogeochemistry*. https://doi.org/10.1007/s10533-023-01084-1

Minasny, B., Berglund, Ö., Connolly, J., Hedley, C., de Vries, F., Gimona, A., Kempen, B., Kidd, D., Lilja, H., Malone, B., McBratney, A., Roudier, P., O'Rourke, S., Rudiyanto, Padarian, J., Poggio, L., ten Caten, A., Thompson, D., Tuve, C., & Widyatmanti, W. (2019). Digital mapping of peatlands – A critical review. In *Earth-Science Reviews* (Vol. 196). https://doi.org/10.1016/j.earscirev.2019.05.014

Minayeva, T., Bragg, O., Cherednichenko, O., Couwenberg, J., van Duinen, G.-J., Giesen, W., Grootjans, A., Grundlin, P.-L., Nikolaev, V., & van der Schaaf, S. (2008). Peatlands and Biodiversity . In *Assessment on Peatlands, Biodiversity and Climate change* (pp. 60–98). Global Environment Centre & Wetlands International.

Minayeva, T., Bragg, O. M., & Sirin, A. A. (2017). Towards ecosystem-based restoration of peatland biodiversity. *Mires and Peat*, *19*. https://doi.org/10.19189/MaP.2013.OMB.150

Moore, P. A., Lukenbach, M. C., Thompson, D. K., Kettridge, N., Granath, G., & Waddington, J. M. (2019). Assessing the peatland hummock–hollow classification framework using high-resolution elevation models: implications for appropriate complexity ecosystem modeling. *Biogeosciences*, *16*(18), 3491–3506. https://doi.org/10.5194/bg-16-3491-2019

Moore, P. D. (2002). The future of cool temperate bogs. *Environmental Conservation*, *29*(1). https://doi.org/10.1017/S0376892902000024

Morelli, T. L., Daly, C., Dobrowski, S. Z., Dulen, D. M., Ebersole, J. L., Jackson, S. T., Lundquist, J. D., Millar, C. I., Maher, S. P., Monahan, W. B., Nydick, K. R., Redmond, K. T., Sawyer, S. C., Stock, S., & Beissinger, S. R. (2016). Managing climate change refugia for climate adaptation. In *PLoS ONE* (Vol. 11, Issue 8). https://doi.org/10.1371/journal.pone.0159909

Munir, T. M., Xu, B., Perkins, M., & Strack, M. (2014). Responses of carbon dioxide flux and plant biomass to water table drawdown in a treed peatland in Northern Alberta: A climate change perspective. *Biogeosciences*, *11*(3). https://doi.org/10.5194/bg-11-807-2014

National Parks and Wildlife Service. (2018). *National raised bog special areas of conservation management plan 2017–2022*. https://www.npws.ie/sites/default/files/general/national-raised-bog-sac-management-plan-en.pdf

Nelson, K., Thompson, D., Hopkinson, C., Petrone, R., & Chasmer, L. (2021). Peatland-fire interactions: A review of wildland fire feedbacks and interactions in Canadian boreal peatlands. In *Science of the Total Environment* (Vol. 769). https://doi.org/10.1016/j.scitotenv.2021.145212

Niemi, G. J., & McDonald, M. E. (2004). Application of ecological indicators. In *Annual Review of Ecology, Evolution, and Systematics* (Vol. 35). https://doi.org/10.1146/annurev.ecolsys.35.112202.130132

Nikou, C., Galatsanos, N. P., & Likas, A. C. (2007). A class-adaptive spatially variant mixture model for image segmentation. *IEEE Transactions on Image Processing*, *16*(4). https://doi.org/10.1109/TIP.2007.891771

Nolan, P., & Flanagan, J. (2020). High resolution climate projections for Ireland - A multi-model ensemble approach. *Forecast*.

Nolan, P., O’Sullivan, J., & McGrath, R. (2017). Impacts of climate change on mid-twenty-first-century rainfall in Ireland: a high-resolution regional climate model ensemble approach. *International Journal of Climatology*, *37*(12), 4347–4363. https://doi.org/10.1002/joc.5091

Norby, R. J., Childs, J., Hanson, P. J., & Warren, J. M. (2019). Rapid loss of an ecosystem engineer: Sphagnum decline in an experimentally warmed bog. *Ecology and Evolution*, *9*(22), 12571–12585. https://doi.org/10.1002/ece3.5722

Nowosad, J., & Stepinski, T. F. (2019). Information theory as a consistent framework for quantification and classification of landscape patterns. *Landscape Ecology*, *34*(9). https://doi.org/10.1007/s10980-019-00830-x

Nungesser, M. K. (2003). Modelling microtopography in boreal peatlands: hummocks and hollows. *Ecological Modelling*, *165*(2–3), 175–207. https://doi.org/10.1016/S0304-3800(03)00067-X

Olofsson, P., Arévalo, P., Espejo, A. B., Green, C., Lindquist, E., McRoberts, R. E., & Sanz, M. J. (2020). Mitigating the effects of omission errors on area and area change estimates. *Remote Sensing of Environment*, *236*. https://doi.org/10.1016/j.rse.2019.111492

Olofsson, P., Foody, G. M., Herold, M., Stehman, S. V., Woodcock, C. E., & Wulder, M. A. (2014). Good practices for estimating area and assessing accuracy of land change. *Remote Sensing of Environment*, *148*, 42–57. https://doi.org/10.1016/j.rse.2014.02.015

Olofsson, P., Foody, G. M., Stehman, S. V., & Woodcock, C. E. (2013). Making better use of accuracy data in land change studies: Estimating accuracy and area and quantifying uncertainty using stratified estimation. *Remote Sensing of Environment*, *129*. https://doi.org/10.1016/j.rse.2012.10.031

Oniga, E., Breaban, A., & Statescu, F. (2018). *Determining the optimum number of ground control points for obtaining high precision results based on UAS images.* https://doi.org/10.3390/ecrs-2-05165

Overland, J. E., Wang, M., Walsh, J. E., & Stroeve, J. C. (2014). Future Arctic climate changes: Adaptation and mitigation time scales. *Earth’s Future*, *2*(2), 68–74. https://doi.org/10.1002/2013EF000162

Paavilainen, E., & Päivänen, J. (1995). *Utilization of Peatlands*. https://doi.org/10.1007/978-3-662-03125-4_2

Pablo Arroyo-Mora, J., Kalacska, M., Inamdar, D., Soffer, R., Lucanus, O., Gorman, J., Naprstek, T., Schaaf, E. S., Ifimov, G., Elmer, K., & Leblanc, G. (2019). Implementation of a UAV–hyperspectral pushbroom imager for ecological monitoring. *Drones*, *3*(1). https://doi.org/10.3390/drones3010012

Padró, J. C., Muñoz, F. J., Ávila, L. Á., Pesquer, L., & Pons, X. (2018). Radiometric correction of Landsat-8 and Sentinel-2A scenes using drone imagery in synergy with field spectroradiometry. *Remote Sensing*, *10*(11). https://doi.org/10.3390/rs10111687

Page, S. E., & Baird, A. J. (2016). Peatlands and Global Change: Response and Resilience. *Annual Review of Environment and Resources*, *41*(1), 35–57. https://doi.org/10.1146/annurev-environ-110615-085520

Palace, M., Herrick, C., DelGreco, J., Finnell, D., Garnello, A., McCalley, C., McArthur, K., Sullivan, F., & Varner, R. (2018). Determining Subarctic Peatland Vegetation Using an Unmanned Aerial System (UAS). *Remote Sensing*, *10*(9), 1498. https://doi.org/10.3390/rs10091498

Pang, Y., Huang, Y., Zhou, Y., Xu, J., & Wu, Y. (2020). Identifying spectral features of characteristics of sphagnum to assess the remote sensing potential of peatlands: A case study in China. *Mires and Peat*, *26*. https://doi.org/10.19189/MaP.2019.OMB.StA.1834

Park, D. S., Newman, E. A., & Breckheimer, I. K. (2021). Scale gaps in landscape phenology: challenges and opportunities. In *Trends in Ecology and Evolution* (Vol. 36, Issue 8). https://doi.org/10.1016/j.tree.2021.04.008

Pasquet, S., Pellerin, S., & Poulin, M. (2015). Three decades of vegetation changes in peatlands isolated in an agricultural landscape. *Applied Vegetation Science*, *18*(2), 220–229. https://doi.org/10.1111/avsc.12142

Patton, D. R. (1975). A diversity index for quantifying habitat “edge.” *Wildlife Society Bulletin*, *3*(4).

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., & Duchesnay, É. (2011). Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research*, *12*.

Pedrotti, E., Rydin, H., Ingmar, T., Hytteborn, H., Turunen, P., & Granath, G. (2014). Fine-scale dynamics and community stability in boreal peatlands: Revisiting a fen and a bog in Sweden after 50 years. *Ecosphere*, *5*(10). https://doi.org/10.1890/ES14-00202.1

Pellerin, S., Mercure, M., Desaulniers, A. S., & Lavoie, C. (2009). Changes in plant communities over three decades on two disturbed bogs in southeastern québec. *Applied Vegetation Science*, *12*(1). https://doi.org/10.1111/j.1654-109X.2009.01008.x

Pelletier, L., Strachan, I. B., Roulet, N. T., Garneau, M., & Wischnewski, K. (2015). Effect of open water pools on ecosystem scale surface-atmosphere carbon dioxide exchange in a boreal peatland. *Biogeochemistry*, *124*(1–3). https://doi.org/10.1007/s10533-015-0098-z

Pinceloup, N., Poulin, M., Brice, M.-H., & Pellerin, S. (2020). Vegetation changes in temperate ombrotrophic peatlands over a 35-year period. *PLOS ONE*, *15*(2), e0229146. https://doi.org/10.1371/journal.pone.0229146

Pouliot, R., Rochefort, L., & Karofeld, E. (2011). Initiation of microtopography in revegetated cutover peatlands. *Applied Vegetation Science*, *14*(2). https://doi.org/10.1111/j.1654-109X.2010.01118.x

Price, J., Evans, C., Evans, M., Allott, T., & Shuttleworth, E. (2016). Peatland restoration and hydrology. In *Peatland Restoration and Ecosystem Services: Science, Policy and Practice*. https://doi.org/10.1017/CBO9781139177788.006

Price, J. S. (2003). Role and character of seasonal peat soil deformation on the hydrology of undisturbed and cutover peatlands. *Water Resources Research*, *39*(9). https://doi.org/10.1029/2002WR001302

Putkiranta, P., Räsänen, A., Korpelainen, P., Erlandsson, R., Kolari, T. H. M., Pang, Y., Villoslada, M., Wolff, F., Kumpula, T., & Virtanen, T. (2024). The value of hyperspectral UAV imagery in characterizing tundra vegetation. *Remote Sensing of Environment*, *308*, 114175. https://doi.org/10.1016/j.rse.2024.114175

Rahman, M. M., McDermid, G. J., Strack, M., & Lovitt, J. (2017). A new method to map groundwater table in peatlands using unmanned aerial vehicles. *Remote Sensing*, *9*(10). https://doi.org/10.3390/rs9101057

Rapinel, S., Rossignol, N., Hubert-Moy, L., Bouzillé, J. B., & Bonis, A. (2018). Mapping grassland plant communities using a fuzzy approach to address floristic and spectral uncertainty. *Applied Vegetation Science*, *21*(4). https://doi.org/10.1111/avsc.12396

Räsänen, A., Aurela, M., Juutinen, S., Kumpula, T., Lohila, A., Penttilä, T., & Virtanen, T. (2020). Detecting northern peatland vegetation patterns at ultra-high spatial resolution. *Remote Sensing in Ecology and Conservation*, *6*(4). https://doi.org/10.1002/rse2.140

Räsänen, A., Elsakov, V., & Virtanen, T. (2019). Usability of one-class classification in mapping and detecting changes in bare peat surfaces in the tundra. *International Journal of Remote Sensing*, *40*(11). https://doi.org/10.1080/01431161.2018.1558376

Räsänen, A., Juutinen, S., Kalacska, M., Aurela, M., Heikkinen, P., Mäenpää, K., Rimali, A., & Virtanen, T. (2020). Peatland leaf-area index and biomass estimation with ultra-high resolution remote sensing. *GIScience & Remote Sensing*, 1–22. https://doi.org/10.1080/15481603.2020.1829377

Räsänen, A., Juutinen, S., Tuittila, E. S., Aurela, M., & Virtanen, T. (2019). Comparing ultra-high spatial resolution remote-sensing methods in mapping peatland vegetation. *Journal of Vegetation Science*, *30*(5). https://doi.org/10.1111/jvs.12769

Räsänen, A., Kuitunen, M., Tomppo, E., & Lensu, A. (2014). Coupling high-resolution satellite imagery with ALS-based canopy height model and digital elevation model in object-based boreal forest habitat type classification. *ISPRS Journal of Photogrammetry and Remote Sensing*, *94*. https://doi.org/10.1016/j.isprsjprs.2014.05.003

Räsänen, A., Manninen, T., Korkiakoski, M., Lohila, A., & Virtanen, T. (2021). Predicting catchment-scale methane fluxes with multi-source remote sensing. *Landscape Ecology*, *36*(4). https://doi.org/10.1007/s10980-021-01194-x

Räsänen, A., Rusanen, A., Kuitunen, M., & Lensu, A. (2013). What makes segmentation good? A case study in boreal forest habitat mapping. *International Journal of Remote Sensing*, *34*(23). https://doi.org/10.1080/01431161.2013.845318

Räsänen, A., Tolvanen, A., & Kareksela, S. (2022). Monitoring peatland water table depth with optical and radar satellite imagery. *International Journal of Applied Earth Observation and Geoinformation*, *112*. https://doi.org/10.1016/j.jag.2022.102866

Räsänen, A., & Virtanen, T. (2019). Data and resolution requirements in mapping vegetation in spatially heterogeneous landscapes. *Remote Sensing of Environment*, *230*, 111207. https://doi.org/10.1016/j.rse.2019.05.026

Rastogi, A., Stróżecki, M., Kalaji, H. M., Łuców, D., Lamentowicz, M., & Juszczak, R. (2019). Impact of warming and reduced precipitation on photosynthetic and remote sensing properties of peatland vegetation. *Environmental and Experimental Botany*, *160*, 71–80. https://doi.org/10.1016/j.envexpbot.2019.01.005

Rawlins, A., & Morris, J. (2010). Social and economic aspects of peatland management in Northern Europe, with particular reference to the English case. *Geoderma*, *154*(3–4). https://doi.org/10.1016/j.geoderma.2009.02.022

Reed, M. S., Young, D. M., Taylor, N. G., Andersen, R., Bell, N. G. A., Cadillo-Quiroz, H., Grainger, M., Heinemeyer, A., Hergoualc'h, K., Gerrand, A. M., Kieft, J., Krisnawati, H., Lilleskov, E. A., Lopez-Gonzalez, G., Melling, L., Rudman, H., Sjogersten, S., Walker, J. S., & Stewart, G. (2022). Peatland core domain sets: building consensus on what should be measured in research and monitoring. *Mires and Peat*, *28*. https://doi.org/10.19189/MaP.2021.OMB.StA.2340

Regan, S., Flynn, R., Gill, L., Naughton, O., & Johnston, P. (2019). Impacts of Groundwater Drainage on Peatland Subsidence and Its Ecological Implications on an Atlantic Raised Bog. *Water Resources Research*, *55*(7). https://doi.org/10.1029/2019WR024937

Regan, S., Swenson, M., O'Connor, M., & Gill, L. (2020). *Ecohydrology, Greenhouse Gas Dynamics and Restoration Guidelines for Degraded Raised Bogs*.

Renou-Wilson, F., Moser, G., Fallon, D., Farrell, C. A., Müller, C., & Wilson, D. (2019). Rewetting degraded peatlands for climate and biodiversity benefits: Results from two raised bogs. *Ecological Engineering*, *127*. https://doi.org/10.1016/j.ecoleng.2018.02.014

Rietkerk, M., Dekker, S. C., Wassen, M. J., Verkroost, A. W. M., & Bierkens, M. F. P. (2004). A Putative Mechanism for Bog Patterning. *The American Naturalist*, *163*(5), 699–708. https://doi.org/10.1086/383065

Riihimäki, H., Luoto, M., & Heiskanen, J. (2019). Estimating fractional cover of tundra vegetation at multiple scales using unmanned aerial systems and optical satellite data. *Remote Sensing of Environment*, *224*. https://doi.org/10.1016/j.rse.2019.01.030

Riutta, T., Laine, J., & Tuittila, E.-S. (2007). Sensitivity of CO2 Exchange of Fen Ecosystem Components to Water Level Variation. *Ecosystems*, *10*(5), 718–733. https://doi.org/10.1007/s10021-007-9046-7

Robb, C., Pickard, A., Williamson, J. L., Fitch, A., & Evans, C. (2023). Peat Drainage Ditch Mapping from Aerial Imagery Using a Convolutional Neural Network. *Remote Sensing*, *15*(2). https://doi.org/10.3390/rs15020499

Robroek, B. J. M., Albrecht, R. J. H., Hamard, S., Pulgarin, A., Bragazza, L., Buttler, A., & Jassey, V. E. (2016). Peatland vascular plant functional types affect dissolved organic matter chemistry. *Plant and Soil*, *407*(1–2), 135–143. https://doi.org/10.1007/s11104-015-2710-3

Robroek, B. J. M., Jassey, V. E. J., Beltman, B., & Hefting, M. M. (2017). Diverse fen plant communities enhance carbon-related multifunctionality, but do not mitigate negative effects of drought. *Royal Society Open Science*, *4*(10). https://doi.org/10.1098/rsos.170449

Robroek, B. J. M., Limpens, J., Breeuwer, A., Crushell, P. H., & Schouten, M. G. C. (2007). Interspecific competition between Sphagnum mosses at different water tables. *Functional Ecology*, *21*(4), 805–812. https://doi.org/10.1111/j.1365-2435.2007.01269.x

Robroek, B. J. M., Limpens, J., Breeuwer, A., & Schouten, M. G. C. (2007). Effects of water level and temperature on performance of four Sphagnum mosses. *Plant Ecology*, *190*(1), 97–107. https://doi.org/10.1007/s11258-006-9193-5

Rocchini, D. (2010). While Boolean sets non-gently rip: A theoretical framework on fuzzy sets for mapping landscape patterns. *Ecological Complexity*, *7*(1). https://doi.org/10.1016/j.ecocom.2009.08.002

Rocchini, D. (2014). Fuzzy species distribution models: A way to represent plant communities spatially. In *Journal of Vegetation Science* (Vol. 25, Issue 2). https://doi.org/10.1111/jvs.12152

Rocchini, D., Foody, G. M., Nagendra, H., Ricotta, C., Anand, M., He, K. S., Amici, V., Kleinschmit, B., Förster, M., Schmidtlein, S., Feilhauer, H., Ghisla, A., Metz, M., & Neteler, M. (2013). Uncertainty in ecosystem mapping by remote sensing. *Computers and Geosciences*, *50*. https://doi.org/10.1016/j.cageo.2012.05.022

Rochefort, L. (2000). Sphagnum —A Keystone Genus in Habitat Restoration. *The Bryologist*, *103*(3), 503–508. https://doi.org/10.1639/0007-2745(2000)103[0503:sakgih]2.0.co;2

Rochefort, L., Isselin-Nondedeu, F., Boudreau, S., & Poulin, M. (2013). Comparing survey methods for monitoring vegetation change through time in a restored peatland. *Wetlands Ecology and Management*, *21*(1), 71–85. https://doi.org/10.1007/s11273-012-9280-4

Rodriguez-Galiano, V. F., Ghimire, B., Rogan, J., Chica-Olmo, M., & Rigol-Sanchez, J. P. (2012). An assessment of the effectiveness of a random forest classifier for land-cover classification. *ISPRS Journal of Photogrammetry and Remote Sensing*, *67*(1), 93–104. https://doi.org/10.1016/j.isprsjprs.2011.11.002

Rydin, H., & Jeglum, J. K. (2013). The Biology of Peatlands. In *The Biology of Peatlands*. Oxford University Press. https://doi.org/10.1093/acprof:osobl/9780199602995.001.0001

Rydin, H., & McDonald, A. J. S. (1985). Tolerance of Sphagnum to water level. *Journal of Bryology*. https://doi.org/10.1179/jbr.1985.13.4.571

Sankey, T. T., McVay, J., Swetnam, T. L., McClaran, M. P., Heilman, P., & Nichols, M. (2018). UAV hyperspectral and lidar data and their fusion for arid and semi-arid land vegetation monitoring. *Remote Sensing in Ecology and Conservation*, *4*(1). https://doi.org/10.1002/rse2.44

Sanz-Ablanedo, E., Chandler, J., Rodríguez-Pérez, J., & Ordóñez, C. (2018). Accuracy of Unmanned Aerial Vehicle (UAV) and SfM Photogrammetry Survey as a Function of the Number and Location of Ground Control Points Used. *Remote Sensing*, *10*(10), 1606. https://doi.org/10.3390/rs10101606

Schaepman-Strub, G., Limpens, J., Menken, M., Bartholomeus, H. M., & Schaepman, M. E. (2009). Towards spatial assessment of carbon sequestration in peatlands: Spectroscopy based estimation of fractional cover of three plant functional types. *Biogeosciences*, *6*(2). https://doi.org/10.5194/bg-6-275-2009

Schouten, M. G. C. (1984). Some aspects of the ecogeographical gradient in Irish ombrotrophic bogs. *Proceedings of the 7th International Peat Congress in Dublin*, 414–432.

Schouten, M. G. C. (1990). Problems of scale in the phytosociology of Irish bogs. In G. Doyle (Ed.), *Ecology and Conservation of Irish Peatlands* (pp. 91–108). Royal Irish Academy.

Schouten, M. G. C. (2002). *Conservation and restoration of raised bogs : geological, hydrological and ecological studies*. The Government Stationary Office.

Schouten, M. G. C., & Kelly, L. (2002). Vegetation. In M. G. C. Schouten (Ed.), *Conservation and Restoration of Raised Bogs: Geological, Hydrological and Ecological Studies* (pp. 110–169). Department of Environment and Local Government.

Seabold, S., & Perktold, J. (2010). Statsmodels: Econometric and Statistical Modeling with Python. *Proceedings of the 9th Python in Science Conference*. https://doi.org/10.25080/majora-92bf1922-011

Shannon, C. E. (1948). A Mathematical Theory of Communication. *Bell System Technical Journal*, *27*(3). https://doi.org/10.1002/j.1538-7305.1948.tb01338.x

Shaposhnikov, D., Revich, B., Bellander, T., Bedada, G. B., Bottai, M., Kharkova, T., Kvasha, E., Lezina, E., Lind, T., Semutnikova, E., & Pershagen, G. (2014). Mortality Related to Air Pollution with the Moscow Heat Wave and Wildfire of 2010. *Epidemiology*, *25*(3), 359–364. https://doi.org/10.1097/EDE.0000000000000090

Shetler, G., Turetsky, M. R., Kane, E., & Kasischke, E. (2008). Sphagnum mosses limit total carbon consumption during fire in Alaskan black spruce forests. *Canadian Journal of Forest Research*, *38*(8), 2328–2336. https://doi.org/10.1139/X08-057

Siewert, M. B., & Olofsson, J. (2020). Scale-dependency of Arctic ecosystem properties revealed by UAV. *Environmental Research Letters*, *15*(9). https://doi.org/10.1088/1748-9326/aba20b

Silvius, M., Joosten, H., & Opdam, S. (2008). Peatlands and People. In *Assessment on Peatlands, Biodiversity and Climate change* (pp. 60–98). Global Environment Centre & Wetlands International.

Simpson, G., Nichol, C. J., Wade, T., Helfter, C., Hamilton, A., & Gibson-Poole, S. (2024). Species-Level Classification of Peatland Vegetation Using Ultra-High-Resolution UAV Imagery. *Drones*, *8*(3). https://doi.org/10.3390/drones8030097

Singh, K. K., & Frazier, A. E. (2018). A meta-analysis and review of unmanned aircraft system (UAS) imagery for terrestrial applications. *International Journal of Remote Sensing*, *39*(15–16). https://doi.org/10.1080/01431161.2017.1420941

Sjögersten, S., Ledger, M., Siewert, M., De La Barreda-Bautista, B., Sowter, A., Gee, D., Foody, G., & Boyd, D. S. (2023). Optical and radar Earth observation data for upscaling methane emissions linked to permafrost degradation in sub-Arctic peatlands in northern Sweden. *Biogeosciences*, *20*(20). https://doi.org/10.5194/bg-20-4221-2023

Soffer, R. J., Ifimov, G., Arroyo-Mora, J. P., & Kalacska, M. (2019). Validation of Airborne Hyperspectral Imagery from Laboratory Panel Characterization to Image Quality Assessment: Implications for an Arctic Peatland Surrogate Simulation Site. *Canadian Journal of Remote Sensing*, *45*(3–4). https://doi.org/10.1080/07038992.2019.1650334

Stace, C. (2019). New flora of the British Isles. In *New flora of the British Isles: Vol. 4th Edition*. https://doi.org/10.2307/4110214

Stachowicz, M., Manton, M., Abramchuk, M., Banaszuk, P., Jarašius, L., Kamocki, A., Povilaitis, A., Samerkhanova, A., Schäfer, A., Sendžikaitė, J., Wichtmann, W., Zableckis, N., & Grygoruk, M. (2022). To store or to drain — To lose or to gain? Rewetting drained peatlands as a measure for increasing water storage in the transboundary Neman River Basin. *Science of the Total Environment*, *829*. https://doi.org/10.1016/j.scitotenv.2022.154560

Steenvoorden, J., Bartholomeus, H., & Limpens, J. (2023). Less is more: Optimizing vegetation mapping in peatlands using unmanned aerial vehicles (UAVs). *International Journal of Applied Earth Observation and Geoinformation*, *117*, 103220. https://doi.org/10.1016/j.jag.2023.103220

Steenvoorden, J., Leestemaker, N., Kooij, D., Crowley, W., Fernandez, F., Schouten, M. G. C., & Limpens, J. (2024). Towards standardised large-scale monitoring of peatland habitats through fine-scale drone-derived vegetation mapping. *Ecological Indicators*, *166*, 112265. https://doi.org/10.1016/j.ecolind.2024.112265

Steenvoorden, J., & Limpens, J. (2023). Upscaling peatland mapping with drone-derived imagery: impact of spatial resolution and vegetation characteristics. *GIScience & Remote Sensing*, *60*(1).

Steenvoorden, J., Limpens, J., Crowley, W., & Schouten, M. G. C. (2022). There and back again: Forty years of change in vegetation patterns in Irish peatlands. *Ecological Indicators*, *145*, 109731. https://doi.org/10.1016/j.ecolind.2022.109731

Stehman, S. V. (2005). Comparing estimators of gross change derived from complete coverage mapping versus statistical sampling of remotely sensed data. *Remote Sensing of Environment*, *96*(3–4). https://doi.org/10.1016/j.rse.2005.04.002

Strack, M., & Waddington, J. M. (2007). Response of peatland carbon dioxide and methane fluxes to a water table drawdown experiment. *Global Biogeochemical Cycles*, *21*(1). https://doi.org/10.1029/2006GB002715

Strack, M., Waddington, J. M., Rochefort, L., & Tuittila, E.-S. (2006). Response of vegetation and net ecosystem carbon dioxide exchange at different peatland microforms following water table drawdown. *Journal of Geophysical Research: Biogeosciences*, *111*(G2). https://doi.org/10.1029/2005JG000145

Strack, M., Waller, M. F., & Waddington, J. M. (2006). Sedge succession and peatland methane dynamics: A potential feedback to climate change. *Ecosystems*, *9*(2). https://doi.org/10.1007/s10021-005-0070-1

Straková, P., Penttilä, T., Laine, J., & Laiho, R. (2012). Disentangling direct and indirect effects of water table drawdown on above- and belowground plant litter decomposition: consequences for accumulation of organic matter in boreal peatlands. *Global Change Biology*, *18*(1), 322–335. https://doi.org/10.1111/j.1365-2486.2011.02503.x

Stralberg, D., Arseneault, D., Baltzer, J. L., Barber, Q. E., Bayne, E. M., Boulanger, Y., Brown, C. D., Cooke, H. A., Devito, K., Edwards, J., Estevo, C. A., Flynn, N., Frelich, L. E., Hogg, E. H., Johnston, M., Logan, T., Matsuoka, S. M., Moore, P., Morelli, T. L., … Whitman, E. (2020). Climate-change refugia in boreal North America: what, where, and for how long? *Frontiers in Ecology and the Environment*, *18*(5), 261–270. https://doi.org/10.1002/fee.2188

Swenson, M. M., Regan, S., Bremmers, D. T. H., Lawless, J., Saunders, M., & Gill, L. W. (2019). Carbon balance of a restored and cutover raised bog: Implications for restoration and comparison to global trends. *Biogeosciences*, *16*(3). https://doi.org/10.5194/bg-16-713-2019

Swindles, G. T., Morris, P. J., Baird, A. J., Blaauw, M., & Plunkett, G. (2012). Ecohydrological feedbacks confound peat-based climate reconstructions. *Geophysical Research Letters*, *39*(11), n/a-n/a. https://doi.org/10.1029/2012GL051500

Swindles, G. T., Morris, P. J., Mullan, D. J., Payne, R. J., Roland, T. P., Amesbury, M. J., Lamentowicz, M., Turner, T. E., Gallego-Sala, A., Sim, T., Barr, I. D., Blaauw, M., Blundell, A., Chambers, F. M., Charman, D. J., Feurdean, A., Galloway, J. M., Gałka, M., Green, S. M., … Warner, B. (2019). Widespread drying of European peatlands in recent centuries. *Nature Geoscience*, *12*(11), 922–928. https://doi.org/10.1038/s41561-019-0462-z

Taillardat, P., Linkhorst, A., Deblois, C. P., Prijac, A., Gandois, L., Tremblay, A., & Garneau, M. (2024). A Carbon Source in a Carbon Sink: Carbon Dioxide and Methane Dynamics in Open-Water Peatland Pools. *Global Biogeochemical Cycles*, *38*(4). https://doi.org/10.1029/2023GB007909

Talbot, J., Richard, P. J. H., Roulet, N. T., & Booth, R. K. (2010). Assessing long-term hydrological and ecological responses to drainage in a raised bog using paleoecology and a hydrosequence. *Journal of Vegetation Science*, *21*(1), 143–156. https://doi.org/10.1111/j.1654-1103.2009.01128.x

Tallis, J. H. (1998). Growth and degradation of British and Irish blanket mires. *Environmental Reviews*, *6*(2). https://doi.org/10.1139/a98-006

Tanneberger, F., Appulo, L., Ewert, S., Lakner, S., Ó Brolcháin, N., Peters, J., & Wichtmann, W. (2021). The Power of Nature-Based Solutions: How Peatlands Can Help Us to Achieve Key EU Sustainability Objectives. In *Advanced Sustainable Systems* (Vol. 5, Issue 1). https://doi.org/10.1002/adsu.202000146

Tanneberger, F., Berghöfer, A., Brust, K., Hammerich, J., Holsten, B., Joosten, H., Michaelis, D., Moritz, F., Reichelt, F., Schäfer, A., Scheid, A., Trepel, M., Wahren, A., & Couwenberg, J. (2024). Quantifying ecosystem services of rewetted peatlands − the MoorFutures methodologies. *Ecological Indicators*, *163*, 112048. https://doi.org/10.1016/j.ecolind.2024.112048

Tanneberger, F., Moen, A., Barthelmes, A., Lewis, E., Miles, L., Sirin, A., Tegetmeyer, C., & Joosten, H. (2021). Mires in europe—regional diversity, condition and protection. *Diversity*, *13*(8). https://doi.org/10.3390/D13080381

The Irish Meteorological Service. (2022, January 6). *Annual Climate Statement for 2021*. https://www.met.ie/annual-climate-statement-for-2021

Timm, B. C., & McGarigal, K. (2012). Fine-scale remotely-sensed cover mapping of coastal dune and salt marsh ecosystems at Cape Cod National Seashore using Random Forests. *Remote Sensing of Environment*, *127*. https://doi.org/10.1016/j.rse.2012.08.033

Tinling, M. A., West, J. J., Cascio, W. E., Kilaru, V., & Rappold, A. G. (2016). Repeating cardiopulmonary health effects in rural North Carolina population during a second large peat wildfire. *Environmental Health*, *15*(1), 12. https://doi.org/10.1186/s12940-016-0093-4

Tuittila, E.-S., Vasander, H., & Laine, J. (2000). Impact of rewetting on the vegetation of a cut-away peatland. *Applied Vegetation Science*, *3*(2). https://doi.org/10.2307/1478999

Turetsky, M. R. (2003). The Role of Bryophytes in Carbon and Nitrogen Cycling. *The Bryologist*, *106*(3), 395–409. https://doi.org/10.1639/05

Turetsky, M. R., Benscoter, B., Page, S., Rein, G., van der Werf, G., & Watts, A. (2015). Global vulnerability of peatlands to fire and carbon loss. *Nature Geoscience*, *8*(1), 11–14. https://doi.org/10.1038/ngeo2325

Turetsky, M. R., Bond-Lamberty, B., Euskirchen, E., Talbot, J., Frolking, S., McGuire, A. D., & Tuittila, E. S. (2012). The resilience and functional role of moss in boreal and arctic ecosystems. In *New Phytologist*. https://doi.org/10.1111/j.1469-8137.2012.04254.x

Turetsky, M. R., Crow, S. E., Evans, R. J., Vitt, D. H., & Wieder, R. K. (2008). Trade-offs in resource allocation among moss species control decomposition in boreal peatlands. *Journal of Ecology*, *96*(6), 1297–1305. https://doi.org/10.1111/j.1365-2745.2008.01438.x

Turetsky, M. R., Donahue, W. F., & Benscoter, B. W. (2011). Experimental drying intensifies burning and carbon losses in a northern peatland. *Nature Communications*, *2*(1), 514. https://doi.org/10.1038/ncomms1523

van Breemen, N. (1995a). How Sphagnum bogs down other plants. *Trends in Ecology & Evolution*, *10*(7), 270–275. https://doi.org/10.1016/0169-5347(95)90007-1 van Breemen, N. (1995b). How Sphagnum bogs down other plants. *Trends in Ecology & Evolution*, *10*(7), 270–275. https://doi.org/10.1016/0169-5347(95)90007-1

van der Schaaf, S. (2002). Bog hydrology. In M. G. C. Schouten (Ed.), *Conservation and Restoration of Raised Bogs: Geological, hydrological and ecological studies* (pp. 54–109). Department of the Environment and Local Government; Staatsbosbeheer.

Van Der Walt, S., Schönberger, J. L., Nunez-Iglesias, J., Boulogne, F., Warner, J. D., Yager, N., Gouillart, E., & Yu, T. (2014). Scikit-image: Image processing in python. *PeerJ*, *2014*(1). https://doi.org/10.7717/peerj.453

Vedaldi, A., & Soatto, S. (2008). Quick shift and kernel methods for mode seeking. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, *5305 LNCS*(PART 4). https://doi.org/10.1007/978-3-540-88693-8_52

Vergouw, B., Nagel, H., Bondt, G., & Custers, B. (2016). *Drone Technology: Types, Payloads, Applications, Frequency Spectrum Issues and Future Developments*. https://doi.org/10.1007/978-94-6265-132-6_2

Verhoeven, J. T. A., & Liefveld, W. M. (1997). The ecological significance of organochemical compounds in Sphagnum. *Acta Botanica Neerlandica*, *46*(2), 117–130. https://doi.org/10.1111/plb.1997.46.2.117

Villoslada, M., Berner, L. T., Juutinen, S., Ylänne, H., & Kumpula, T. (2024). Upscaling vascular aboveground biomass and topsoil moisture of subarctic fens from Unoccupied Aerial Vehicles (UAVs) to satellite level. *Science of The Total Environment*, *933*, 173049. https://doi.org/10.1016/j.scitotenv.2024.173049

Virtanen, T., & Ek, M. (2014). The fragmented nature of tundra landscape. *International Journal of Applied Earth Observation and Geoinformation*, *27*(PARTA). https://doi.org/10.1016/j.jag.2013.05.010

Vitt, D., & House, M. (2021). Bryophytes as key indicators of ecosystem function and structure of northern peatlands. *Bryophyte Diversity and Evolution*, *43*(1). https://doi.org/10.11646/bde.43.1.18

Waddington, J. M., Griffis, T. J., & Rouse, W. R. (1998). Northern Canadian wetlands: Net ecosystem CO2 exchange and climatic change. *Climatic Change*, *40*(2). https://doi.org/10.1023/A:1005468920206

Waddington, J. M., Kellner, E., Strack, M., & Price, J. S. (2010). Differential peat deformation, compressibility, and water storage between peatland microforms: Implications for ecosystem function and development. *Water Resources Research*, *46*(7). https://doi.org/10.1029/2009WR008802

Waddington, J. M., Morris, P. J., Kettridge, N., Granath, G., Thompson, D. K., & Moore, P. A. (2015). Hydrological feedbacks in northern peatlands. *Ecohydrology*, *8*(1), 113–127. https://doi.org/10.1002/eco.1493

Waddington, J. M., & Roulet, N. T. (1996). Atmosphere-wetland carbon exchanges: Scale dependency of CO 2 and CH 4 exchange on the developmental topography of a peatland. *Global Biogeochemical Cycles*, *10*(2), 233–245. https://doi.org/10.1029/95GB03871

Walker, T. N., Garnett, M. H., Ward, S. E., Oakley, S., Bardgett, R. D., & Ostle, N. J. (2016). Vascular plants promote ancient peatland carbon loss with climate warming. *Global Change Biology*, *22*(5), 1880–1889. https://doi.org/10.1111/gcb.13213

Walker, T. N., Ward, S. E., Ostle, N. J., & Bardgett, R. D. (2015). Contrasting growth responses of dominant peatland plants to warming and vegetation composition. *Oecologia*. https://doi.org/10.1007/s00442-015-3254-1

White, L., McGovern, M., Hayne, S., Touzi, R., Pasher, J., & Duffe, J. (2020). Investigating the potential use of RADARSAT-2 and UAS imagery for monitoring the restoration of Peatlands. *Remote Sensing*, *12*(15). https://doi.org/10.3390/RS12152383

Wichmann, S., Brander, L., Schäfer, A., Schaafsma, M., Van Beukering, P., Tinch, D., & Bonn, A. (2016). Valuing peatland ecosystem services. In *Peatland Restoration and Ecosystem Services: Science, Policy and Practice*. https://doi.org/10.1017/CBO9781139177788.017

Wieder, R. K., Vitt, D. H., & Benscoter, B. W. (2006). Boreal Peatland Ecosystems, Ecological Studies 188. In *Springer*.

Wilson, D., Farrell, C., Mueller, C., Hepp, S., & Renou-Wilson, F. (2013). Rewetted industrial cutaway peatlands in western Ireland: a prime location for climate change mitigation? *Mires and Peat*, *11*.

Wilson, J. B., & Agnew, A. D. Q. (1992). Positive-feedback Switches in Plant Communities. In *Advances in Ecological Research* (pp. 263–336). https://doi.org/10.1016/S0065-2504(08)60149-X

Xu, J., Morris, P. J., Liu, J., & Holden, J. (2018). PEATMAP: Refining estimates of global peatland distribution based on a meta-analysis. *CATENA*, *160*, 134–140. https://doi.org/10.1016/j.catena.2017.09.010

Yang, J., He, Y., & Weng, Q. (2015). An Automated Method to Parameterize Segmentation Scale by Enhancing Intrasegment Homogeneity and Intersegment Heterogeneity. *IEEE Geoscience and Remote Sensing Letters*, *12*(6). https://doi.org/10.1109/LGRS.2015.2393255

Yaniv, Z., Lowekamp, B. C., Johnson, H. J., & Beare, R. (2018). SimpleITK Image-Analysis Notebooks: a Collaborative Environment for Education and Reproducible Research. *Journal of Digital Imaging*, *31*(3). https://doi.org/10.1007/s10278-017-0037-8

Yu, Z. C. (2011). Holocene carbon flux histories of the world’s peatlands. *The Holocene*, *21*(5), 761–774. https://doi.org/10.1177/0959683610386982

Yu, Z. C., Loisel, J., Brosseau, D. P., Beilman, D. W., & Hunt, S. J. (2010). Global peatland dynamics since the Last Glacial Maximum. *Geophysical Research Letters*, *37*(13), n/a-n/a. https://doi.org/10.1029/2010GL043584

Zeh, L., Igel, T. M., Schellekens, J., Limpens, J., Bragazza, L., & Kalbitz, K. (2020). Vascular plants affect properties and decomposition of moss-dominated peat, particularly at elevated temperatures. *Biogeosciences Discussions*, 1–29. https://doi.org/10.5194/bg-2019-503

Zeh, L., Limpens, J., Erhagen, B., Bragazza, L., & Kalbitz, K. (2019). Plant functional types and temperature control carbon input via roots in peatland soils. *Plant and Soil*, *438*(1–2), 19–38. https://doi.org/10.1007/s11104-019-03958-6

Zhang, H., Väliranta, M., Swindles, G. T., Aquino-López, M. A., Mullan, D., Tan, N., Amesbury, M., Babeshko, K. v., Bao, K., Bobrov, A., Chernyshov, V., Davies, M. A., Diaconu, A.-C., Feurdean, A., Finkelstein, S. A., Garneau, M., Guo, Z., Jones, M. C., Kay, M., … Zhao, Y. (2022). Recent climate change has driven divergent hydrological shifts in high-latitude peatlands. *Nature Communications*, *13*(1), 4959. https://doi.org/10.1038/s41467-022-32711-4

Zlinszky, A., & Kania, A. (2016). WILL IT BLEND? VISUALIZATION AND ACCURACY EVALUATION OF HIGH-RESOLUTION FUZZY VEGETATION MAPS. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *XLI-B2*. https://doi.org/10.5194/isprs-archives-xli-b2-335-2016

Chapter 8

Summaries and end matter

Summary

Northern peatlands play a disproportionally large role in the global carbon balance due to the massive amount of carbon they store in peat as well as ongoing sequestration. Peatlands also contain unique plant and animal biodiversity, regulate biodiversity and climate extremes surrounding their borders and are crucial for water storage and flood mitigation. Ecosystem-wide monitoring of the functions associated with these important ecosystem services is therefore needed to better inform policy and management and to facilitate carbon financing schemes. Vegetation composition and structure are recognised ecological indicators for peatland functions like carbon sequestration, water storage and quality and plant biodiversity. Consequently, mapping vegetation patterns and associated functions with unmanned aerial vehicles or drones could be ideal for ecosystem-wide monitoring, as they can capture the fine and heterogeneous nature of peatland vegetation patterns but at the same time can cover relatively large areas.

However, the decadal dynamics of peatland vegetation patterns are not well understood, and it is unsure whether vegetation patterns change at time-scales that facilitate ecosystem-wide monitoring using remote sensing analyses with drones. Besides, drone-based remote sensing is a new scientific discipline, and consistent documentation and comparisons of different drone-based mapping approaches for use in peatlands are virtually non-existent. This is problematic, because drone-based remote sensing can quickly become unnecessarily costly, complex, time-consuming and computationally heavy depending on the adopted approach. These factors hamper the general applicability of drones in the field, as well as upscaling of drone-based approaches for mapping vegetation patterns and their functions to the spatial scales at which they matter most, clearly stressing the demand and responsibility for comparative testing.

To respond to these research needs, I aimed to provide novel and comprehensive insights into the strengths, limitations and requirements of drones in large-scale mapping of peatland vegetation patterns. This way, I ultimately strove to advance the development of accurate, efficient and standardised monitoring workflows that various users could use or build upon to assess the dynamics of peatland vegetation patterns in space and time, as well as the functions and services they represent. To this end, I iteratively designed and refined a remote sensing mapping approach that could at length be upscaled to map plant functional types, microforms and habitats in whole Irish peatlands using only consumer-grade drone imagery products.

We show that mapping approaches with consumer-grade drone imagery could play a central role in monitoring peatland functions because of the ease by which even consumer-grade drones can capture and process spectral, spatial and topographical information with unprecedented levels of detail. These factors were all highly important in characterising peatland vegetation patterns. We achieved generally high accuracy and efficiency in all of our studied peatlands, especially with the most current version of the mapping approach. Through its development, we initially show that peatland vegetation patterns can accurately be mapped with drones, and that vegetation patterns can undergo significant surface drying in only ~40 years (Chapter 2). These results stressed the importance of developing such mapping approaches even further. However, because our initial mapping efforts were highly inefficient, we strove to improve this by flying at higher altitudes, optimising the grouping of image pixels into relevant objects (segmentation), and optimising the number of ground-reference samples needed to create accurate vegetation pattern maps (Chapter 3). We found that flying at the maximum legal flight altitude of 120m, which strikingly reduces the number of images captured per area, still resulted in high accuracy maps compared to flying at 60m and 20m. Besides, we saw that a total number of 250–500 ground-reference samples and creating segments of minimally 0.25m by 0.25m still resulted in accurate maps. This was crucial, because without compromising on accuracy, our mapping approach suddenly became at least a factor 19–22 times more efficient than in Chapter 2 (Chapter 3).

While the results of Chapter 3 were already a notable improvement, we found that this mapping approach was still not able to be upscaled to whole peatlands because of the extremely high spatial detail of the drone imagery, which was still 2.7cm at 120m flight altitude. In fact, even with a fast computer our analyses always crashed using areas of more than a few hectares. Consequently, we evaluated to what extent spatial resolution of imagery could be reduced and tweaked (resampled) even further to improve mapping efficiency without losing accuracy. We also evaluated whether differences in the organisation of vegetation patterns among peatlands could affect this optimisation (Chapter 4). In general, we saw that microforms and plant functional types could still be mapped accurately when spatial resolutions were resampled to 0.5m and 0.25m respectively. Besides, we saw that more degraded peatlands with more homogeneous vegetation patterns could be mapped with coarser spatial resolutions than peatlands with more intricate and finely distributed vegetation patterns. This is highly important, because not only did we reduce data volumes for our mapping approach by at least a factor 86 (at 0.25m), but we also show that mapping efforts targeting changes in peatland functioning should be adapted to conditions demanding the highest spatial resolution, which may be notably different between peatlands (Chapter 4).

By implementing the findings of our mapping optimisation from Chapter 2, 3 and 4, we could now start upscaling our mapping approach to the scale of whole peatlands, ranging in size between 35–124ha (Chapter 5). We found that plant functional types, microforms and habitats could all be classified accurately and consistently at the scale of whole peatlands using consumer-grade drone-derived imagery products. Our results show that studies like these that aim to elucidate pivotal aspects of drone-based remote sensing for accurate and efficient vegetation pattern mapping can certainly help in moving towards standardisation practices. Besides, by iteratively expanding and refining this mapping approach, we were able to identify, address and/or solve at least some of the numerous challenges that caused inconsistencies, inaccuracies and/or inefficiencies throughout all peatlands in the study area (Chapter 6). This is needed to ensure that at least plant functional types, microforms and habitats can continue to be mapped accurately and consistently. Still, given predominant focus on ecosystem services in peatlands, potential answers to questions related to vegetation pattern classification should be driven by most optimally linking form to functions. I argue that we currently require much more development of frameworks for standardising the measuring and reporting of peatland functions. Knowing better what to measure and how to measure it is critical to start converging data collection efforts towards a more standardised outcome (Chapter 6).

All in all, my thesis provides clear evidence that consumer-grade drone-based mapping approaches hold great potential for monitoring peatland functions through their vegetation patterns. However, peatlands are incredibly complex ecosystems, and we show that aiming to map them adequately requires critical consideration of all aspects of a mapping approach. Besides, the tremendous variety in peatland characteristics worldwide means that mapping their vegetation patterns with a single approach is practically impossible. Yet, we should still develop unified processes by which the peatland community can accurately and efficiently standardise mapping approaches at least between regions. Given recent and expected developments in drone technology, I therefore argue we should put more effort into developing, evaluating and optimising drone-based and hybrid drone-satellite mapping approaches that are specifically designed to test their accuracy and efficiency for monitoring vegetation patterns and their associated functions in a variety of peatlands and peatland types, as this is what will ultimately determine their applicability in the field. The results from this thesis provide comprehensive and novel insights into the multiple requirements for large-scale mapping of peatland vegetation patterns on which future drone studies can build to further develop, evaluate and optimise both drone-based and hybrid drone-satellite mapping approaches. This will slowly but steadily bring the goal of assessing the dynamics of peatland functions and their services all over the globe ever closer.

Samenvatting

Noordelijke venen spelen een onevenredig grote rol in de mondiale koolstofbalans door de enorme hoeveelheid koolstof die ze opslaan in veen en door vastlegging die nog gaande is. Veengebieden bevatten ook een unieke biodiversiteit van planten en dieren, reguleren de biodiversiteit en klimaatextremen rondom hun grenzen en zijn cruciaal voor wateropslag en het beperken van overstromingen. Ecosysteembrede monitoring van de functies die geassocieerd worden met deze belangrijke ecosysteemdiensten is daarom nodig om beleid en beheer beter te informeren en om koolstoffinancieringsregelingen te kunnen verantwoorden. Vegetatiesamenstelling en vegetatiestructuur zijn erkende ecologische indicatoren voor veenfuncties zoals koolstofopslag, wateropslag, waterkwaliteit en plantenbiodiversiteit. Het in kaart brengen van vegetatiepatronen en bijbehorende functies met onbemande luchtvaartuigen of drones zou daarom ideaal kunnen zijn voor ecosysteembrede monitoring. Dit omdat drones de fijne en heterogene aard van vegetatiepatronen in venen kunnen vastleggen en tegelijkertijd relatief grote gebieden kunnen bestrijken.

De tijdschaal waarop vegetatiepatronen in venen veranderen word echter niet goed begrepen, en het is daarom onzeker of vegetatiepatronen veranderen op tijdschalen die ecosysteembrede monitoring met behulp van drones mogelijk maken. Bovendien zijn analyses met behulp van drones een nieuwe wetenschappelijke discipline, en zijn consistente documentaties en vergelijkingen van verschillende drone-gebaseerde karteringsmethoden voor gebruik in veengebieden vrijwel onbestaand. Dit is problematisch omdat analyses met behulp van drones al snel onnodig duur, complex, tijdrovend en rekenintensief kunnen worden afhankelijk van de gekozen aanpak. Deze factoren belemmeren de algemene toepasbaarheid van drones in de praktijk, evenals het opschalen van drone-gebaseerde benaderingen voor het in kaart brengen van vegetatiepatronen en hun functies naar de ruimtelijke schalen waarop ze het meest van belang zijn. Dit benadrukt duidelijk de vraag naar en de verantwoordelijkheid voor vergelijkende analyses en testen.

Om aan deze onderzoeksbehoeften te voldoen, wilde ik nieuwe en uitgebreide inzichten verschaffen in de sterke punten, beperkingen en vereisten van drones bij het grootschalig in kaart brengen van vegetatiepatronen in venen. Op deze manier streefde ik uiteindelijk naar de ontwikkeling van nauwkeurige, efficiënte en gestandaardiseerde monitoringmethoden die verschillende belanghebbenden zouden kunnen gebruiken of waarop ze zouden kunnen voortbouwen om de dynamiek van vegetatiepatronen in ruimte en tijd te beoordelen, evenals de functies en diensten die ze vertegenwoordigen. Daartoe heb ik iteratief een methode ontworpen en verfijnd die op termijn opgeschaald kan worden om functionele plantentypen, microvormen en habitats in hele Ierse venen in kaart kan brengen. Hierbij werd alleen gebruik gemaakt van producten die gecreëerd zijn met informatie die vergaard is met consumentendrones.

We laten zien dat karteringsmethoden met consumentendrones een centrale rol zouden kunnen spelen bij het monitoren van de functies van venen, omdat zelfs consumentendrones gemakkelijk spectrale, ruimtelijke en topografische informatie met een ongekend detailniveau kunnen vastleggen en verwerken. Al deze factoren waren van groot belang bij het karakteriseren van vegetatiepatronen in onze bestudeerde venen. We bereikten over het algemeen een hoge nauwkeurigheid en efficiëntie in al onze bestudeerde venen, vooral met de meest recente versie van de karteringsaanpak. Door de ontwikkeling ervan laten we in eerste instantie zien dat vegetatiepatronen nauwkeurig in kaart gebracht kunnen worden met drones, en dat vegetatiepatronen in slechts ~40 jaar een aanzienlijke oppervlakte-uitdroging kunnen ondergaan (Hoofdstuk 2). Deze resultaten benadrukten het belang van het verder ontwikkelen van onze karteringsmethode. Omdat de eerste versie van onze karteringsmethode echter zeer inefficiënt was, hebben we geprobeerd dit te verbeteren door op grotere hoogtes te vliegen, het groeperen van beeldpixels in relevante objecten (segmentatie) te optimaliseren, en het aantal grondreferentiepunten dat nodig is om nauwkeurige kaarten te maken te optimaliseren (Hoofdstuk 3). We ontdekten dat vliegen op de maximaal toegestane vlieghoogte van 120m, wat het aantal vastgelegde beelden per gebied opvallend vermindert, nog steeds resulteerde in kaarten met een hoge nauwkeurigheid in vergelijking met vliegen op 60m en 20m. Bovendien zagen we dat een totaal aantal van 250-500 grondreferentiesamples en het creëren van segmenten van minimaal 0.25m bij 0.25m nog steeds resulteerde in nauwkeurige kaarten. Dit was cruciaal, want zonder concessies te doen aan de nauwkeurigheid, werd onze karteringsaanpak minstens een factor 19-22 efficiënter dan in Hoofdstuk 2 (Hoofdstuk 3).

Hoewel de resultaten van Hoofdstuk 3 al een aanzienlijke verbetering waren, ontdekten we dat deze karteringsaanpak nog steeds niet kon worden opgeschaald naar hele venen vanwege het extreem hoge ruimtelijk detail van de dronebeelden. Deze was namelijk nog steeds 2.7cm bij 2.7cm per pixel op 120m vlieghoogte. Zelfs met een snelle computer liepen onze analyses altijd vast bij gebieden van meer dan een paar hectare. Daarom hebben we geëvalueerd in hoeverre de ruimtelijke resolutie van de beelden nog verder verlaagd en verfijnd (geresampled) kon worden om de efficiëntie van de kartering te verbeteren zonder aan nauwkeurigheid te verliezen. We hebben ook geëvalueerd of verschillen in de organisatie van vegetatiepatronen tussen venen van invloed zouden kunnen zijn op deze optimalisatie (Hoofdstuk 4). Over het algemeen zagen we dat microvormen en functionele planttypen nog steeds nauwkeurig in kaart konden worden gebracht als de ruimtelijke resoluties werden geresampled naar respectievelijk 0.5 m en 0.25 m. Daarnaast zagen we dat meer gedegradeerde veengebieden met homogenere vegetatiepatronen gekarteerd konden worden met grovere ruimtelijke resoluties dan veengebieden met meer ingewikkelde en fijnverdeelde vegetatiepatronen. Dit is van groot belang, omdat we niet alleen de datavolumes voor onze karteringsaanpak met minstens een factor 86 (bij 0.25m) hebben teruggebracht, maar ook hebben laten zien dat karteringsinspanningen gericht op veranderingen in het functioneren van venen moeten worden aangepast aan omstandigheden die de hoogste ruimtelijke resolutie vereisen, die aanzienlijk kan verschillen tussen venen (Hoofdstuk 4).

Door de bevindingen van onze karteringsoptimalisatie uit Hoofdstuk 2, 3 en 4 te implementeren, konden we nu beginnen met het opschalen van onze karteringsaanpak naar de schaal van hele venen, variërend in grootte tussen 35-124ha (Hoofdstuk 5). We ontdekten dat functionele plantentypen, microvormen en habitats allemaal nauwkeurig en consistent konden worden geclassificeerd op de schaal van hele venen met behulp van beeldproducten die gecreëerd waren met consumentendrones. Onze resultaten laten hiermee zien dat studies zoals deze die gericht zijn op het ophelderen van cruciale aspecten van analyses met behulp van drones voor nauwkeurige en efficiënte kartering van vegetatiepatronen zeker kunnen helpen bij de ontwikkeling naar standaardisatie. Door deze karteringsaanpak iteratief uit te breiden en te verfijnen, konden we bovendien ten minste enkele van de talloze uitdagingen identificeren, aanpakken en/of oplossen die inconsistenties, onnauwkeurigheden en/of inefficiënties veroorzaakten in alle venen in het studiegebied (Hoofdstuk 6). Dit is nodig om ervoor te zorgen dat ten minste functionele planttypen, microvormen en habitats nauwkeurig en consistent in kaart kunnen worden blijven gebracht. Echter, gezien de overheersende focus op ecosysteemdiensten in venen moeten potentiële antwoorden op vragen met betrekking tot de classificatie van vegetatiepatronen worden gestuurd door de meest optimale koppeling tussen vorm en functies. Ik beargumenteer dat er momenteel veel meer behoefte is aan de ontwikkeling van kaders voor het standaardiseren van het meten en rapporteren van veenfuncties. Beter weten precies wat je moet meten en hoe je het moet meten is cruciaal om te beginnen met het samenkomen van de inspanningen op het gebied van gegevensverzameling naar een meer gestandaardiseerde uitkomst (Hoofdstuk 6).

Al met al levert mijn proefschrift duidelijk bewijs dat het in kaart brengen van venen met behulp van drones een groot potentieel heeft voor het monitoren van veengerelateerde functies via hun vegetatiepatronen. Venen zijn echter ongelooflijk complexe ecosystemen, en we laten zien dat het adequaat in kaart te brengen hiervan een kritische beschouwing vereist van alle aspecten van een karteringsaanpak. Bovendien betekent de enorme variatie in veenkenmerken wereldwijd dat het in kaart brengen van hun vegetatiepatronen met één enkele benadering praktisch onmogelijk is. Toch moeten we uniforme processen ontwikkelen waarmee de veengemeenschap karteringsmethoden nauwkeurig en efficiënt kan standaardiseren, in ieder geval tussen regio’s. Gezien de recente en verwachte ontwikkelingen op het gebied van dronetechnologie, pleit ik er daarom voor om meer energie te steken in het ontwikkelen, evalueren en optimaliseren van karteringsmethodes op basis van drones en hybride drone-satelliet die specifiek ontworpen zijn om hun nauwkeurigheid en efficiëntie te testen voor het monitoren van vegetatiepatronen en de bijbehorende functies in een verscheidenheid aan venen en veentypen. Dit zal namelijk uiteindelijk hun toepasbaarheid in het veld bepalen. De resultaten van dit proefschrift bieden uitgebreide en nieuwe inzichten in de vele vereisten voor het op grote schaal in kaart brengen van vegetatiepatronen in venen. Toekomstige studies kunnen hierop voortbouwen om karteringsmethodes op basis van drones of hybride drone-satelliet verder te ontwikkelen, evalueren en optimaliseren. Dit zal langzaam maar zeker het doel van het beoordelen van de dynamiek van veenfuncties en hun ecosysteemdiensten over de hele wereld steeds dichterbij brengen.

About the author

Jasper started his PhD at Wageningen University in 2020, but his fascination for research started long before that. When he was young, he wanted to work as a veterinarian, or become a ranger in the Amsterdamse Waterleidingduinen.

Still, he studied Future Planet Studies at the University of Amsterdam, which is an interdisciplinary bachelor's degree focused on global sustainability issues. Here he pursued a major in Earth Science and took additional courses on glaciology and geomorphology during a minor at the University of Edinburgh.

He continued exploring his interests in research of ecosystems and their dynamics in the Master Earth Science at the University of Amsterdam, where he specialised in the research-track Geo-Ecological Dynamics. He carried out his MSc thesis at the University of Idaho in Moscow, Idaho. This project focused on the role of unburned vegetation islands as fire-refugia for the persistence and recovery of the greater sage-grouse in the sagebrush ecosystems of south-eastern Oregon. The project was later published in a peer-reviewed journal.

After a two-year appointment as a junior-lecturer for his former bachelor's degree Future Planet Studies, he applied for a PhD programme in peatland ecology at Wageningen University. He could never have guessed that this ecosystem would become one of his greatest obsessions.

In his free time, he enjoys bouldering, being outdoors, fermentation, concerts, playing guitar, videogames, sharing his love for peatlands and cooking for those dear in his life. In October 2024, Jasper will start a two-year post-doc position within the Plant Ecology & Nature Conservation Group at Wageningen University in cooperation with Uppsala University in Sweden. He will continue developing remote sensing approaches to map peatland vegetation patterns as ecological indicators.

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Steenvoorden, J., Bartholomeus, H., & Limpens, J. (2023). Less is more: Optimizing vegetation mapping in peatlands using unmanned aerial vehicles (UAVs). *International Journal of Applied Earth Observation and Geoinformation*, 117, 103220. https://doi.org/10.1016/j.jag.2023.103220

Steenvoorden, J., & Limpens, J. (2023). Upscaling peatland mapping with drone-derived imagery: impact of spatial resolution and vegetation characteristics. *GIScience & Remote Sensing*, 60(1). https://doi.org/10.1080/15481603.2023.2267851

Steenvoorden, J., Leestemaker, N., Kooij, D., Crowley, W., Fernandez, F., Schouten, M. G. C., & Limpens, J. (2024). Towards standardised large-scale monitoring of peatland habitats through fine-scale drone-derived vegetation mapping. *Ecological Indicators*, 166, 112265. https://doi.org/10.1016/j.ecolind.2024.112265

Other

Steenvoorden, J., Meddens, A. J. H., Martinez, A. J., Foster, L. J., & Kissling, W. D. (2019). The potential importance of unburned islands as refugia for the persistence of wildlife species in fire-prone ecosystems. *Ecology and Evolution*, 9(15).

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A big thank you to all my colleagues at the PEN group. While the many working climate analyses and insights discovery tests might suggest otherwise, I know (and I think we secretly all do) PEN as a warm research group where everyone is equal and where we all mingle effortlessly. **David,** thank you for being at its helm, because I think you are an important aspect of this, and I think you are a great group leader! Even though my own research deviates quite a lot from the dominant research lines that PEN represents (looking at you, pollinators!), I have always felt supported and valued for my own research. This is even further emphasised by the fact that I was not in the office, and lived a nomads live when I was there. Thanks also specifically to **Gerda** and **Petra** for all the administrative, financial and logistic support during my PhD and in preparation for my post-doc project. The occasions were many. I am very glad that I can continue to stay at PEN for at least another three years, and I hope to share many more fun, interesting, and educational moments together.

Within PEN, three other colleagues deserve a special mention. **Rúna**, **Abbey** and **Enahu**. In a research group where peatlands (and tundra) are severely underrepresented, it is always great to be able to discuss new perspectives about “heterogeneous landscapes” and swoon over peatlands with likeminded geeks. Rúna, aside from an innate likeability because we share a similar Future Planet Studies history at PEN, I also look up to you when it comes to doing research. The fact that you were about 2.5 years ahead of me meant that I could cheat a bit by looking at your great work for inspiration and motivation, and this has helped me a lot through my PhD process. Abbey, it was great to have a partner in crime throughout the last years of my PhD, for help on my graphs, papers, overly lengthy presentations and even if it was just to bitch about literally everything on this planet. You were a much needed and appreciated sounding board. And Enahu, I am glad there is even another ex-Future Planet Studies student at PEN, and I am also glad you are one of the few peatland mappers around the world. I like to think we think similarly about ecosystems, and I am sure we will be able to work closer together in the near future and perform some great peatland science! Thank you both also for taking up the responsibility to be my paranymphs as well.

A very big shoutout to my best friend and roommate **Daniël**. I do not even know where to start but to mention that you have been so involved in my project from the start that you were even rightfully included as a co-author on my last paper. I think there is no person in this world who is such an expert on a field of science while not even being formally part of it as you are! Not only are you my best buddy, but also a tireless sparring partner, and with your truly limitless data science knowledge you have had a large responsibility in ensuring the robustness of the mapping approach that we developed during this thesis. That surely deserves a mention here as well. I sincerely hope we can keep working on great science together!

Adding to this is a thank you to my other roommates. **Jochem** and **Sven**, I do not know where to start. I cannot even recount the many things you have helped me with and the many times you have done this during my thesis. From simply helping me create better graphs in Python, to guiding me in my work-life balance (TAKE THE DAY OFF!!!), to saving me from the brink of insanity when my computer crashed again; I could not have wished for a better support system these last four years. And all it cost me in return was a bit of good cooking! Furthermore, I think I can say that I have truly brainwashed you both into loving peatlands nearly as much as I do. This has even gone so far that we are currently making a professional documentary about peatlands together with our mutual friends. I think this says enough about our level of friendship.

Papa. Ultimately, I think you were at the basis of all of this. Not only were you a motivation for me to learn about nature when I was younger, but you were also responsible for the fact that I could effortlessly go to school and university. As a result, I could focus fully on the things that interested me, and open doors that would perhaps never have opened for me. I very gratefully and respectfully made us of that mostly unconditional freedom and flexibility. I look forward to many more adventures with you in nature together.

Mama. While I know that is not always easy to follow what I am doing, especially when things get too technical, I know that you are proud of what I am doing, predominantly because I follow my heart. You are as much a supporter as you are a critic, especially when it comes to work-life balance, and being ‘zen’. You always taught me to stay close to myself in all situations, and while this is sometimes still a challenge for me, I think I am getting better at it every year. Thanks for always being a listening ear when I needed one.

Opa Rokus and oma Jo. Ever since I was born, you were by my side, and ever since I was old enough to go to school, you were my greatest supporters. Oma, it always makes me emotional to hear you say how proud Rokus would have been to see me pursue this path, and how much he would have liked to see me graduate. But I secretly know he does from above! You are the kindest and most supportive grandma I could have wished for, and I am so grateful for that. This thesis is also partially for you!

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born on 27 July 1995 in Haarlem, The Netherlands

has successfully fulfilled all requirements of the
educational PhD programme of SENSE.

Wageningen, 11 October 2024

SENSE coordinator PhD education

Dr Ir Peter Vermeulen

The SENSE Director

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The SENSE Research School declares that **Jasper Steenvoorden** has successfully fulfilled all requirements of the educational PhD programme of SENSE with a work load of 43.1 EC, including the following activities:

SENSE PhD Courses

- Environmental research in context (2020)
- Research in context activity: 'Creating a professional documentary peatlands in the Netherlands, about the relationship between people and their landscape' (2024)

Other PhD and Advanced MSc Courses

- Introduction to Machine Learning, PE&RC (2021)
- Dynamic Models in R: Programming, parameter estimation and model selection, PE&RC (2021)
- Fire in the landscape; introduction to biophysical aspects, WIMEK (2021)

Management and Didactic Skills Training

- Supervising four MSc student with thesis (2022-2024)
- Teaching in the field practicals of the BSc course 'Landscape excursions' (2022-2024)
- Teaching in the MSc course 'Plant, Vegetation, and Systems Ecology' (2021 & 2023)
- Guest Lecture on Wildfires at First year Future Planet Studies at University of Amsterdam (2021)
- Writing popular or newspaper articles for the general public (2022)

Oral Presentations

- *Microform succession in raised bogs over a 40-year time-period.* Living Bog End of Project Conference, 8-9 March , 2022, Athlone, Ireland
- *Mapping fine-scale vegetation patterns as ecological indicators for peatland biodiversity and carbon sequestration.* European Geosciences Union, 23-28 April 2023, Vienna, Austria
- Van Veenmos Tot Vogelvlucht, Hoogveenherstel in Nederland. De Groene Voorouder, 15th of March 2024, Radio Kootwijk, The Netherlands
- *Towards efficient and standardised large-scale monitoring of peatland habitats through fine-scale drone-derived vegetation mapping.* European Geosciences Union, 14-20 April 2024, Vienna, Austria

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