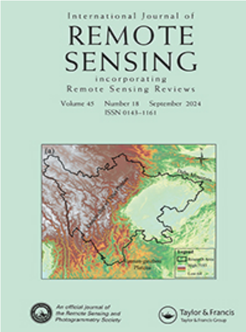

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Enhancing peatland monitoring through multisource remote sensing: optical and radar data applications

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ABSTRACT

Peatlands play a pivotal role in global carbon cycling and the conservation of biodiversity even though they cover a small fraction of the Earth's terrestrial surface. These ecosystems are, however, increasingly vulnerable due to climate change impacts and anthropogenic activities, leading to significant degradation in many areas. This review compiles and analyses various studies that employ remote sensing for comprehensive peatland mapping and monitoring. Remote sensing offers detailed insights into critical peatland features, including the classification of peatland vegetation, assessment of water table dynamics, mapping of vegetation condition and diversity and the estimation of carbon stocks. Furthermore, the review delineates the utility of remote sensing in monitoring the recovery processes of restored peatlands, highlighting the scarcity of long-term studies. It also emphasizes the potential of integrating hyperspectral, multispectral and SAR data as well as cross-scale analyses. Concluding with future directions, the review underscores the necessity for enhanced upscaling techniques, integration of multi-sensor data and the application of modelling to enrich our understanding and management of peatland ecosystems.

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remote sensing; peatland; biodiversity; water table dynamics; hyperspectral

1. Introduction

Peatlands are unique wetland ecosystems that constantly store vast amounts of carbon in the form of plant residues that, due to the absence of oxygen in the water-saturated soil, decompose at very low rates. Although peatlands cover only 3–4% of the Earth's land surface, these ecosystems are responsible for storing around 21–30% of the world's soil carbon (Hilbert, Roulet and Moore 2000; Jackson et al. 2017; Leifeld and Menichetti 2018; Minasny et al. 2023; Monteverde et al. 2022; UNEP 2022).

While the term 'peatland' is used globally, there is no universally accepted definition (Lourenco, Fitchett and Woodborne 2023). Generally, a peatland is considered an

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area where peat, an organic-rich soil composed of at least 30% organic material (by dry weight), which has naturally accumulated at the surface (Lourenco, Fitchett and Woodborne 2023; Tanneberger et al. 2021). The presence of vegetation is not a determining factor in this definition. The term encompasses 'mires', which are types of peatlands where peat formation is ongoing (Joosten and Clarke 2002; Tanneberger et al. 2021). For broader categorization, especially in the context of carbon-rich soils, the term 'organic soil' is also used. This approach is also adopted by the Intergovernmental Panel on Climate Change (IPCC), refers to soils with substantial organic matter content.

Peatlands are dynamic ecosystems characterized by complex interactions between hydrology, plant community structure and carbon cycling processes. The key to their functionality lies in their hydrological regime, whose large water bodies have been identified as important regulators for regional climate (Leifeld and Menichetti 2018) and water systems (Nordbeck and Hogl 2023). High water table levels minimize oxygen availability, reducing decomposition rates and thereby promoting carbon accumulation. However, these anoxic conditions also favour the production and emission of methane, an important greenhouse gas (Bhullar et al. 2013). The biogeochemical processes are accompanied by significant acidification and leaching of nutrients, leaving many peatlands as nutrient-poor, acidic environments where only specialist species survive. This has led to the development of unique floristic and faunistic species communities in peatlands of this planet, with many species being endemic and endangered (Minayeva, Bragg and Sirin 2017). The distribution of peatland species is closely aligned with the hydrological dynamics. Many plant species in these ecosystems are particularly vulnerable to changes in moisture, temperature, nutrient availability and redox conditions. Environmental changes, such as changes in temperature and water table can therefore significantly influence the plant communities (Dieleman et al., 2015; Limpens et al., 2008). While faunistic species would respond directly to environmental changes and indirectly to the changes in the plant communities, the related variations in primary production rates and the decomposition of plant matter would significantly impact the carbon dynamics of the ecosystem (Y. Zhou et al. 2023). Climate change would therefore induce multiple intertwined responses in peatlands (Mozafari et al. 2023), most of which would lead to deterioration of these unique ecosystems.

The carbon storage mechanism in peatlands depends on the anaerobic conditions in the waterlogged soil. In the absence of oxygen and at low pH values, many of the abundant soil organisms cannot contribute to the decomposition of organic matter, which is continuously entering the soil from the active aboveground vegetation. The organic matter accumulates and undergoes a very slow degradation process which leads to the formation of distinguishable forms of peat, the terminal stages of which qualify peat, after being excavated and dried, as effective fuel for heating and cooking. Early civilizations have therefore exploited peatlands for this fuel source, leaving a typical cultural landscape behind. At later stages, agriculture expanded and required more land, for which farmers started to drain the peatlands. The lowered water table now allowed oxygen to infiltrate, a starting point for a still ongoing degradation process. The consequent massive carbon loss has led to large peatland areas to sink in, while surrounding areas with mineral soil remained at the original elevation, exposing the peatland to a higher risk of temporal flooding (Ikkala et al. 2021; Kreyling et al. 2021; Tanneberger et al.

2021). Currently, an estimated 11.7% of peatlands are considered being degraded (UNEP 2022).

The impact of carbon release from drained peatlands is considerable, influencing the global carbon balance (Loisel et al. 2021; Qiu et al. 2020). Peatland conservation and restoration therefore hold significant importance in the international context, as outlined by various global policy frameworks and conventions (EU Habitats directive, Natura 2000 network; EU Biodiversity strategy for 2030). The United Nations Convention to Combat Desertification (UNCCD) recognizes peatlands as vital for land use planning and integral to the climate change agenda, primarily due to their carbon storage capabilities and the potential for reducing greenhouse gas emissions through restoration efforts. This sentiment is echoed in the United Nations Framework Convention on Climate Change (UNFCCC), which includes peatlands in its Kyoto Protocol, the Paris Climate Agreement and national greenhouse gas reporting. The IPCC also provides technical recommendations for reporting on greenhouse gas emissions from peatlands. The Ramsar Convention on Wetlands, the 2030 Agenda for Sustainable Development and the UN Environment Assembly resolution on the conservation and sustainable management of peatlands all underscore the role of peatlands in achieving climate change mitigation targets and biodiversity conservation (FAO 2020). To effectively support the conservation and restoration commitments outlined and sustainable management of peatlands, it is necessary to enhance the understanding of the feedback mechanisms involved. For this purpose, comprehensive data analysis and modelling are essential. Both approaches benefit from the availability of large data sets.

Field data gathering in peatlands can be challenging. Waterlogging and often dense vegetation cover, and their often remote and inaccessible locations make fieldwork labour-intensive, slow and costly. Consequently, using remote sensing to map and monitor peatlands presents a practical alternative (Millard et al. 2020; Minasny et al. 2019). Remote sensing, with its ability to provide timely, accurate and large-scale data, has emerged as an invaluable tool in assessing peatland hydrological, carbon cycle as well as vegetation dynamics, condition (e.g. degradation) and restoration (Minasny et al. 2023). Although some of the processes, such as root system dynamics, microbial activity, sedimentation not been a focus of remote sensing-based studies, remote sensing-based data has been widely used for mapping peatland extent, as well as vegetation characteristics and diversity (Cabezas et al. 2015; Mcmorrow et al. 2004; Steenvoorden and Limpens 2023). As interactions between hydrological dynamics, vegetation characteristics and carbon cycling are critical for maintaining ecosystem services and determining the response of peatlands to environmental changes, monitoring these processes are essential for a better understanding of the system. In this context, remote sensing derived proxies can provide insights into hydrological processes, changes in vegetation cover and production and can be used as inputs to derive greenhouse gas (GHG) emissions, thereby enhancing our ability to monitor and manage these dynamic ecosystems. Optical sensors provide information regarding vegetation properties, such as composition as well as condition, such as moisture content. Nevertheless, the data from optical sensors can be affected by clouds, lowering the number of images available for the analysis. Radar data, on the other hand, are independent of weather conditions and, with their sensitivity to moisture and roughness of the surface, can provide complementary information to optical data.

The primary aim of this review is to provide an in-depth analysis of remote sensing-based methods for peatland monitoring, particularly focusing on following critical aspects: vegetation and biodiversity mapping, water table dynamics assessment, SOC and carbon flux assessment and monitoring of restoration. Although a few reviews exist (Czapiewski and Szumińska 2022; Lees et al. 2018), most of them focus on the topic of assessment of GHG fluxes based on remote sensing data. Considering that in recent years there have been more studies with an increasing focus on mapping of biodiversity, as well as on the assessment of soil organic carbon, water table dynamics and monitoring of restoration, our review places its focus on these specific aspects. Firstly, the review will explore the latest advancements in remote sensing technologies, including satellite, airborne and UAV data, and how they are utilized to map and monitor peatlands. This includes assessing the effectiveness of these methods in identifying different plant species, monitoring vegetation health and detecting changes in biodiversity. Secondly, the review focuses on the capabilities of remote sensing in accurately mapping and understanding water table fluctuations, which are essential for comprehending the hydrological processes in peatlands. Lastly, the review targets the quantification of SOC stocks using remote sensing, evaluating the accuracy and reliability of these methods in estimating carbon sequestration and release in peatlands. Throughout the review, the challenges and limitations of current remote sensing approaches are critically examined, along with suggestions for future advancements to enhance peatland monitoring.

2. Methods

Structured queries on the Web of Science (http://apps.webofknowledge.com/.), using combinations of key terms and their synonyms related to Peatland, remote sensing, and earth observation (Table 1) were conducted from 1 October 2023 to 10 May 2024. The search was restricted to the results of articles and reviews. The analysis of these documents involved focusing on research where essential phrases appeared, and the papers where the utilization of satellite, airborne or Unoccupied Aerial Vehicles (UAV) data for mapping and monitoring peatlands were not a central theme were excluded. Additionally, we employed a snowball sampling technique to identify relevant papers from references in the literature, which, although not discovered through the systematic search, were significant to the primary objectives of this review. The initial query resulted in 291 papers. These papers were examined for their thematic content. Publications that focused on broad-scale classification, where peatland was just one of the many classes, were excluded from further analysis. Papers that used only the Digital Elevation Model (DEM) were also omitted, even if 'remote sensing' was listed as a keyword. Approximately 50 papers concentrated on fire assessment and post-fire recovery in peatland areas; these

Table 1. Search query design.

AND			
OR	Peatland	Classif	Remote*sens
	Bog	Model	Optical
	Fen	Monitor	Radar
		Map	Hyperspectral
			UAV
			SAR

were also excluded from further discussion. The resulting set of studies (227 articles and reviews; Supplementary 1) was then analysed to identify the main research directions for the use of remotely sensed data for the three key thematic areas.

In this review, we not only focused on general information extracted from the studies but specific aspects such as different thematic and methodological focus, including (1) focus area, (2) sensor type and platform used and (3) thematic focus of the study has been investigated.

3. Results

The review shows a significant increase in the use of remote sensing methods in peatland research (Figure 2). This increase is attributed to the greater availability of remote sensing data sets, such as Sentinel 1 and 2 coupled with the increase in the use of hyperspectral sensors. These advancements have enabled more comprehensive and varied analyses in peatland studies. The typical elements analysed using satellite data include classification and identification of peatland vegetation, monitoring of peatland state and restoration impacts, water table depth analysis and the estimation of carbon in peatlands. It was observed that the majority of the studies utilized satellite-based remote sensing data, while airborne data represented the least used platform, as shown in Figure 3.

The geographic spread of the studies is uneven across the globe. Generally, there is a greater emphasis on mapping and monitoring peatlands in temperate and boreal regions, while tropical peatland mapping has received less attention. Most of the research concentrates on specific countries like Canada, UK, Germany, Indonesia and Finland, with only a handful of studies conducting extensive cross-country analyses, such as those targeting Northern Peatlands (Supplement 1). This focus is likely influenced by the prominent peatland expanses in these areas. For example, vast boreal peatlands are found in Canada. In Europe, roughly all areas north of 50° latitude is notable for its significant peat bogs and mires (Montanarella, Jones and Hiederer 2006). In Indonesia, tropical peatlands have received significant attention due to their large area and crucial ecological role. However, it is crucial to acknowledge that much of the research conducted in these countries often focuses on small, selected areas rather than expansive, landscape-scale investigations (Figure 1).

3.1. Applications of remote sensing in peatland vegetation mapping and biodiversity assessment

The assessment of vegetation condition and biodiversity in peatlands using remote sensing is vital, as the floristic composition and health of peatland vegetation are key indicators of ecosystem integrity and functionality, reflecting the impacts of changes in moisture, temperature and nutrient conditions. This dynamic interplay affects primary production and decomposition, in turn influencing carbon flux and habitat quality (Harris, Charnock and Lucas 2015). For instance, a higher proportion of vascular plants is associated with increased soil respiration, contributing significantly to ecosystem carbon fluxes (Walker et al. 2016). Vegetation compositions in peatlands not only affect the overall net ecosystem exchange but also influence how carbon fluxes respond to environmental changes and extreme events (Lees et al. 2018). Furthermore, the abundance

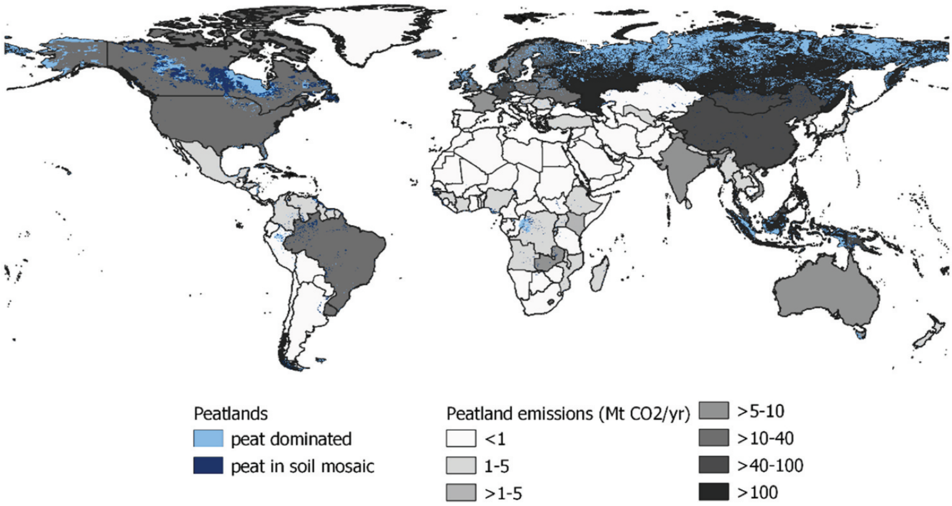

Figure 1. Peatland extent based on global peatland map (Greifswald Mire Centre 2022) and peatland emissions per country data gathered from (Greifswald Mire Centre 2015).

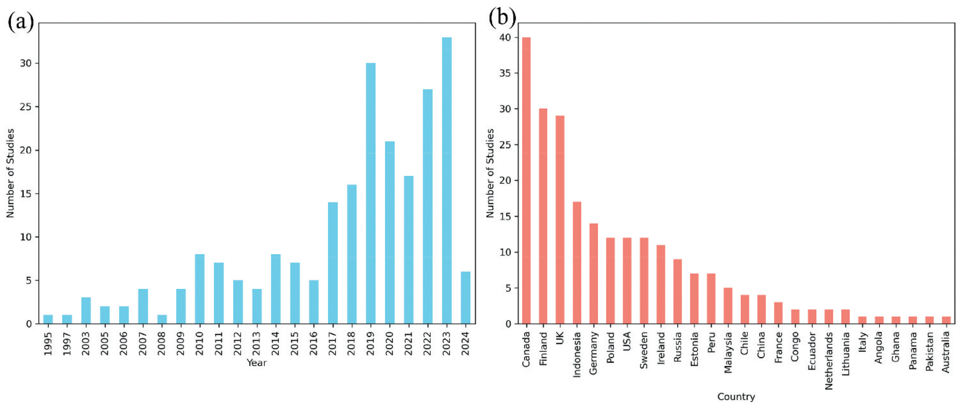

Figure 2. Number of studies with the use of remote sensing for peatland monitoring per year (a) and per country (b).

and composition of species can be used as an indicator of the success of peatland management and rewetting activities (Arasumani et al. 2023; Beyer et al. 2019). Another proxy that can be derived from remote sensing is plant phenology, which may be considered an indicator of the changing climate and the adaptation of species to new environmental conditions (Antala et al. 2022).

The use of Sentinel-2 data has been instrumental in mapping vegetation phenology, as demonstrated by (J. P. Arroyo-Mora, Kalacska, Soffer, et al. 2018; Garisoain et al. 2023). These studies were conducted in diverse areas, characterized by different sizes (3.7 ha to 2800 ha respectively). Derived information on phenology is important for not only plant traits such as Leaf Area Index (LAI) but also for identifying patterns and main growth areas of dominant species such as sphagnum. This in turn can help to identify the optimal

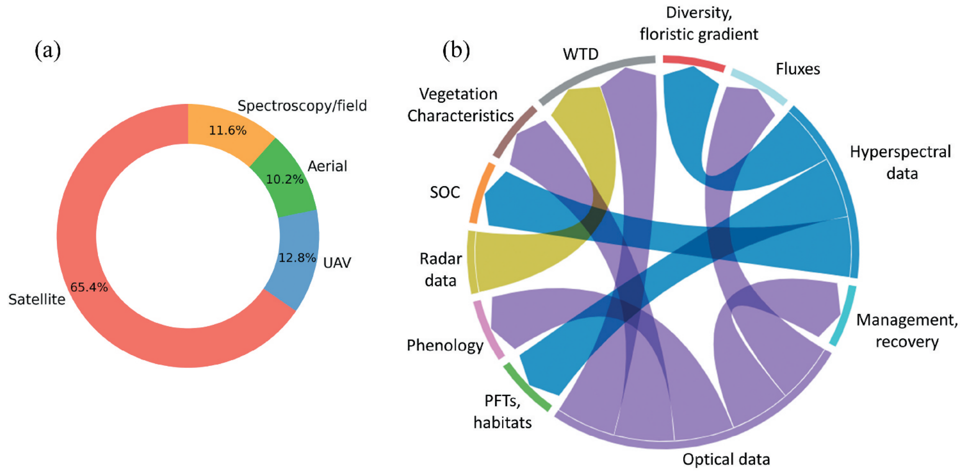

Figure 3. (a) the proportion of satellite, airborne, UAV and Plot level spectroscopy and (b) network graph showing the use of different sensors for specific thematic focus more than 70% of the papers focused on vegetation properties, some of which used vegetation based proxies for the assessment of processes such as restoration or derivation of metrics such as above ground biomass and carbon. Around 10% of papers focused on SOC and greenhouse gas fluxes, and another 10% on water table depth and hydrological dynamics. Twenty-nine of the papers used hyperspectral data.

timing for image acquisition, which requires detailed information about the spectral characteristics of natural species over the growing season. The variation of spectral response with the phenological cycle has been extensively studied by (Cole, McMorrow and Evans 2014). They compared point-based hyperspectral measurements and derived phenological change using narrowband vegetation indices (Red Edge Position, Photochemical Reflectance Index, Plant Senescence Reflection Index and Cellulose Absorption Index) to identify the best windows that show the highest phenological change in the spectra for an upland peatland undergoing restoration in Northern England. Along with optical data, SAR data were also used for peatland vegetation characterization (Bourgeau-Chavez et al. 2017; Karlson et al. 2019; Merchant et al. 2017; White et al. 2017).

In addition, other remote sensing-based metrics have been derived using satellite and UAV-based data (Knoth et al. 2013; Steenvoorden, Bartholomeus and Limpens 2023), such as phenometrics, LAI, Above Ground Biomass (AGB), as well as Plant Functional Types (PFTs), habitat types, and communities. However, there are challenges reported when directly mapping peatland PFTs from remote sensing data (Schaepman-Strub et al. 2008; Schmidtlein et al. 2012) primarily due to the difficulties in identifying characteristic spectral signatures using traditional spectral- or pixel-based approaches (Harris, Charnock and Lucas 2015).

Multispectral and hyperspectral data were used to map peatland floristic gradients (Harris, Charnock and Lucas 2015), peat health (Stuart et al. 2022) and vegetation composition after rewetting (Frick et al. 2011). Field or simulated spectroscopy, as used by (Schaepman-Strub et al. 2008), estimated the fractional cover and AGB. Erudel et al. (2017) utilized in situ hyperspectral measurements to evaluate the potential of hyperspectral data in separating and classifying habitats. They tested three methods based on the similarity of spectral reflectance and supervised classification based on vegetation indices and spectral ranges. Their findings highlighted the effectiveness of various VIs and several distance metrics for the identification of peatland species. Furthermore, functional types and traits as well as peatland plant communities were also characterized (Kattenborn et al. 2017; McPartland et al. 2019; Thomas et al. 2003) using airborne hyperspectral data. Investigations into biomass and plant functional types were also conducted by Pang et al. (2022), with the use of field spectroscopy data. Airborne hyperspectral data were also used for mapping biotopes, as well as assessing moisture and fertility gradients in peatlands (Middleton et al. 2012).

Similarly, UAV-based hyperspectral data, for instance, was effectively utilized by Räsänen et al. (2020) for mapping peatland vegetation AGB and LAI. Moreover, a variety of datasets and their combinations, including PlanetScope, UAV data and LiDAR data, have been employed for the classification of habitat types and plant communities, as evidenced by (Beyer et al. 2019; Räsänen et al. 2019). LAI and AGB were also estimated using UAV-based LiDAR, hyperspectral and RGB sensors (Assiri et al. 2023). They found that LiDAR was the most useful variable for AGB estimation with the most accurate model including indices retrieved from both LiDAR and hyperspectral data. The study of foliar chlorophyll, as explored by (Kalacska, Lalonde and Moore 2015), further underscores the range of applications for hyperspectral data. In the realm of habitat-type assessment, the combination of UAV and Worldview data proved effective, as shown by (Räsänen et al. 2019). Although they have highlighted the usefulness of ultra high-resolution data with cm level pixel size (0.05–0.08 m) for mapping fine-scale variability in peatland vegetation and showed potential for assessing spatial dynamics in biogeochemical processes such as carbon cycling, they also acknowledge the challenges of similar assessment over large geographical areas due to limitations of image acquisition and data processing. Likewise, the investigation into plant composition and species diversity by (McPartland et al. 2019) added valuable insights on the use of field and aerial hyperspectral data for assessing the peatland ecological response to changes in temperatures and CO2 levels in boreal peatlands.

Although less, airborne (Mcmorrow et al. 2004) and spaceborne hyperspectral applications are also emerging (Arasumani et al. 2023), with recent studies assessing the potential of multi-date PRISMA data for peatland vegetation mapping. Mcmorrow et al. (2004) highlighted the effectiveness of SWIR data and spectral indices for peat composition assessment.

Other applications include the use of Sentinel-2 and Sentinel-1 time series to assess the impact of restoration activities (Ball et al. 2023). Here, the Sentinel-2 data were compared with an aerial imagery as well, with satellite data showing higher accuracy and potential for large-scale monitoring of restoration activities using remote sensing derived proxies of vegetation, soil moisture and water table depth. Similarly, degradation and further restoration were observed using L-band radar data (Z. Zhou et al. 2019) and Landsat data (Torabi Haghighi et al. 2018). The vegetation response to varying conditions has also been observed by (Bryant and Baird 2003) based on spectroscopy data. Franke, Keuck and Siegert (2012) showcased the use of multi-temporal high-resolution RapidEye data for large-scale assessment of grassland use intensity, highlighting the importance of seasonality in selecting adequate observation dates.

Moderate and coarse scale remote sensing data has also been used for the assessment of disturbances and condition in peatlands (Artz et al. 2019; Connolly et al. 2011; Pflugmacher, Krankina and Cohen 2007). Furthermore, the study by Cabezas et al. (2015) demonstrated how multiscale remote sensing data, including data from the Landsat 8 and Pleiades, could be utilized to classify and evaluate different vegetation types and their associated carbon storage capacities. This approach allowed for the differentiation of vegetation cover and health based on the spectral indices derived from the optical data, enabling a more accurate estimation of aboveground carbon stocks influenced by different management practices. One of the main challenges in remote sensing based peatland characterization is the structural complexity of peatlands. Additionally, the limitations of these techniques stem from the temporal and spatial resolutions of remote sensing data, as well as from in situ plant diversity and mixing (Erudel et al. 2017).

3.2. Water table depth assessment

Water Table Depth (WTD) in peatlands is an essential factor in terms of emissions of the three main greenhouse gases (Bechtold et al. 2014; Evans et al. 2021; Minasny et al. 2023). Low water levels lead to more aerated soil pore space, resulting in emissions of CO2 and nitrous oxide (N2O) (Bechtold et al. 2014; Evans et al. 2021). In contrast, high groundwater levels promote the absorption of these gases because waterlogging prevents oxygen from penetrating the soil and organic material from plants is not entirely broken down. However, rising water levels can lead to methane (CH4) emissions (Bechtold et al. 2014; Evans et al. 2021).

Remote Sensing sensors can only penetrate the outermost surface of soil, with optical and thermal sensors monitoring only the soil surface or vegetation cover and microwave sensors using X-, C- and L-bands monitoring the first few centimetres of the soil (Babaeian et al. 2019; Li et al. 2021) and can therefore not directly measure WTD. However, due to the high hydraulic conductivity of peatlands, there is a close connection between the groundwater level and the surface moisture of the soil, as capillary forces bring water from the groundwater table into unsaturated zone (Dettmann and Bechtold 2016).

Soil moisture and water content can be assessed by optical sensors either directly from the spectral signal of soils or indirectly from plant reflection (Burdun, Bechtold, Sagris, Lohila, et al. 2020), as well as from thermal emission and microwave backscattering (Sadeghi et al. 2017). For peatlands covered with vegetation year round, optical remote sensing using indices relying on water absorption bands has been a way to monitor soil moisture. For example, Harris and Bryant (2009) demonstrated that spectral indices based on (NIR) and shortwave infrared (SWIR) can be used to derive information on the near-surface moisture of peatlands dominated by *Sphagnum* mosses from airborne multi-spectral imagery. Likewise, hyperspectral images have been used to estimate WTD by employing a narrow band water index as a proxy for vegetation (Kalacska et al. 2018).

Further studies used the combination of optical and thermal data for WTD based on the interpretation of the pixel distribution between Land Surface Temperature (LST) and a vegetation index (Sadeghi et al. 2017), such as Thermal-Optical TRApezoid Model

(TOTRAM). Further variation of this model is the Optical TRApezoid Model (OPTRAM) which relies on optical satellite imagery by replacing the LST parameter with SWIR transformed reflectance (STR) (Sadeghi et al. 2017). It is thus making use of the physical linear relationship between STR and soil moisture content, as well as the relationship between root soil water content and vegetation water content (Sadeghi et al. 2017). The OPTRAM approach was used to retrieve temporal water table dynamics for northern fen and bog peatlands with Landsat, MODIS and Sentinel-2 data and has been found useful, especially for sites without or with tree cover density below 50% for shallow to moderate water tables (Burdun et al. 2020a, 2020b, 2023; Räsänen, Tolvanen and Kareksela 2022). TOTRAM, on the other hand, failed to provide good estimation results for northern peat bogs, which may be due to the very variable solar energy available at these latitudes largely determining vegetation growth. It might therefore not be a suitable indicator for representing vegetation stress but may produce better results in climatic zones, in which water and not energy is the limiting factor for vegetation growth (Burdun, Bechtold, Sagris, Komisarenko, et al. 2020).

Due to SAR sensitivity to dielectric properties of surfaces, there has been an increase in the studies with the use of different datasets to estimate the groundwater-level dynamics in peatlands at different degradation stages. For example, Bechtold et al. (2018) used ENVISAT Advanced Synthetic Aperture Radar (ASAR), while later studies used Sentinel-1 (Asmuß, Bechtold and Tiemeyer 2019; Lees, Artz, et al. 2021; Räsänen, Tolvanen and Kareksela 2022; Toca et al. 2023). While using C-band radar has generally been found to have a high potential for deriving WTD, there are some factors limiting an accurate estimation. For example, low radar backscatter may be caused by a very shallow WTD during flooding and consequent soil inundation as well as by deep WTD in drier soil conditions. Asmuß, Bechtold and Tiemeyer (2019) found the best correlation for a medium-high WTD between −0.60 m and −0.20 m.

In addition to sensitivity to moisture, vegetation leads to variations in backscatter not only based on moisture content but also because of biomass and dense canopies and structure. Volume scattering of the SAR signal typically arises as a result of the rough surface structure of leaves, branches and stems. To account for this impact of vegetation growth, some studies have used additional equations based on vegetation indices from optical satellite data to correct for it (Dabrowska-Zielinska et al. 2018). The influence of vegetation on the backscatter signal depends on site management, for example, some grasslands might face sudden drops in biomass, likely influencing the correlation with WTD (Bechtold et al. 2018). The time of year and climate conditions have an impact on the backscatter as well – including parameters to account for seasonality of water regimes in the WTD prediction were found to improve the result as they found higher backscatter values in autumn and winter when WTD was lower and lower backscatter in spring and summer, when the WTD was high for Northern Scottish blanket bogs (Toca et al. 2023).

Räsänen, Tolvanen and Kareksela (2022) tested different optical (Landsat, Sentinel-2) and C-band Sentinel-1 data for assessing WTD using random forest regressions run for different study sites and found optical-based features (e.g. SWIR based metrics) better performing in most cases. Furthermore, large differences have been observed in the performance of the regression models between and within peatland habitat types.

Further assessments and integration of L band data could be suitable and allow for more accurate monitoring as its longer wavelength allows for even better penetration of vegetation and soil penetration (Li et al. 2021; Räsänen, Tolvanen and Kareksela 2022). However, some of the data, such as Soil Moisture and Ocean Salinity (SMOS) and Soil Moisture Active Passive (SMAP) missions, have coarse spatial resolution which does not make it useful for peatland monitoring (Burdun, Bechtold, Sagris, Lohila, et al. 2020). Peatlands are often heterogeneous and small in size, so there is a need for adequate spatial resolution when monitoring them (Bechtold et al. 2018; Burdun, Bechtold, Sagris, Lohila, et al. 2020). Nevertheless, these data can be used for large-scale assessment. In addition to satellite-based WTD and moisture assessment, UAV (Isoaho et al. 2023; Kameoka et al. 2021; Rahman et al. 2017) and other high-resolution data (Toca et al. 2022) have been also reported as useful for this task. For their study, area in Finland (Isoaho et al. 2023) used MicaSence Altum-PT sensor to collect multispectral and thermal imagery and derived several vegetation indices and used linear mixed models to explain the variability of water table levels. Kameoka et al. (2021) used RGB and thermal data for a similar assessment in tropical peatland in Indonesia. Rahman et al., 3017 used different approaches and first classified surface water based on Aeryon HDZoom30 optical imagery and then used the data on water levels and digital elevation and geostatistical models derived continuous information.

3.3. Soil organic carbon and greenhouse gas fluxes

Although fewer studies have focused on the use of remote sensing for SOC assessment in peatlands, with more focus on other systems, such as croplands (Castaldi et al. 2019; Gholizadeh et al. 2021) they show considerable potential for the use of multi- and hyperspectral data. In case of peatlands, studies emerged that use visible and near-infrared spectroscopy for quantifying SOC as well as nitrogen content in peatlands (Mendes and Sommer 2023; Mendes et al. 2022) over Europe using available LUCAS survey data. Other studies used ALOS PALSAR and Landsat data in combination with field data for estimating peat thickness and carbon stocks (Crezee et al. 2022) and SPOT data (Akumu and McLaughlin 2014). A similar study used Sentinel-1 data for peat thickness and carbon stock assessment (Fiantis et al. 2024).

Lopatin et al. (2019) tested the use of aboveground vegetation attributes based on UAV hyperspectral data as proxies to predict peatland belowground C stocks. This was based on the relations between remotely detectable vegetation attributes (i.e. vegetation height, aboveground biomass, species richness and floristic composition of vascular plants) and C stocks. Nevertheless, estimating belowground carbon stocks in peatlands using optical data and canopy height measurements is a complex task due to data limitations such as the challenges in providing belowground information from optical sensors, rather than methodological shortcomings. Algorithms such as random forests and support vector machines known for handling non-linear relationships and effectively modelling canopy reflectance, height and carbon gradients generally offer more accuracy than traditional linear models. Despite their capabilities, deep learning methods like Convolutional Neural Networks are increasingly used in remote sensing applications due to their performance (Odebiri et al. 2023; Odebiri, Odindi and Mutanga 2021) and can further improve the predictive capabilities of the models for reliable belowground carbon stock estimation. In addition, integrating ecological insights with remote sensing could enhance mapping precision and deepen ecosystem function understanding. However, more research is needed to identify aboveground indicators that can reduce soil sampling for belowground carbon stock model calibration.

Other approaches used remote sensing data (Landsat, ALOS PALSAR) to first map the peatland area and then combine the results with an extensive soil coring dataset to produce the map of soil carbon stocks (Bourgeau-Chavez et al. 2021; Hribljan et al. 2017). In another example, spectral indices from RapidEye satellite data, LiDAR and electrical conductivity data for SOCstocks mapping (de Sousa Mendes et al. 2023).

Airborne hyperspectral imagery was used to map biophysical variables related to C dynamics, such as CO2 uptake efficiency (J. P. Arroyo-Mora, Kalacska, Soffer, Moore, et al. 2018). Significantly more studies have used remote sensing data for the assessment of carbon budgets (Park, Takeuchi and Ichii 2020), which include components such as GPP (Czapiewski and Szumińska, 2022; Kross et al. 2013, 2013; Lees, Khomik et al., 2021; Y. Zhou et al. 2023), ecosystem respiration (Burdun et al. 2021; Junttila et al. 2021), methane emissions (Lehmann et al. 2016; Tucker et al. 2022) and dissolved organic carbon (Cherukuru et al. 2021; Parry et al. 2015). The majority of these studies rely on MODIS data. Nevertheless, Landsat (Burdun et al. 2021; Crichton et al. 2015; Schubert et al. 2010) and Sentinel data have been used for this as well. These studies provide an opportunity to further assess the impact of rewetting (Y. Zhou et al. 2023).

4. Discussion

This review reveals a large number of research focusing on peatland monitoring that employs a variety of remote sensing data and methodologies. Predominantly, these studies aim to identify the most effective data sets, timing of the acquisition and algorithms for mapping vegetation composition, habitat types and communities. There is a growing trend in using SAR and optical time series for assessing water table depth. Additionally, emerging research focuses on evaluating peatland restoration patterns. This is often done by deriving proxies and classifying the abundance and composition of species which can be further used as an indicator of the peatland management and rewetting activities.

WTD and hydrological dynamics were successfully monitored using optical data. Several studies have also demonstrated the effectiveness of radar for this purpose. This is in agreement with Czapiewski et al. (2022), who also emphasized the usefulness of Sentinel-1 for WTD assessment. A smaller number of studies utilized aboveground vegetation proxies for SOC assessment. This link might stem from the positive correlation between vegetation and SOC, particularly relevant in peatlands where soil is often covered by vegetation (Lamichhane et al., 2019), making it hard to create bare soil composites and extraction of soil spectra when relying only on optical data. While Remote Sensing cannot directly measure GHG emissions, it can provide proxies that, when combined with models, help estimate these emissions. Remote Sensing based data can be used to derive inputs necessary for GHG emission models, particularly those related to vegetation cover and productivity (Lees et al. 2018).

In many studies hyperspectral imaging showed better performance than multispectral data, which can be due to the capability of hyperspectral data to capture finer spectral signatures of vegetation than multispectral sensors (Kalacska, Lalonde and Moore 2015; Räsänen et al. 2020) Most of the studies highlighted the importance of SWIR band and derived indices both for mapping vegetation and moisture assessment (Bubier, Rock and Crill 1997; Burdun, Bechtold, Sagris, Lohila, et al. 2020). Nevertheless, still many studies also successfully used VNIR (500–900 nm) data. It is important to note that the application of hyperspectral imaging at large scales can be challenging. This is partly because many studies utilizing hyperspectral data were conducted with in situ measurements using spectroradiometers, which may limit their scalability. Additionally, hyperspectral data from satellites are not as widely available as multispectral data from platforms like Landsat and Sentinel, and they often have coarser spatial resolution compared to these multispectral datasets. Moreover, platforms such as Landsat and Sentinel offer much better temporal resolution, enabling continuous mapping and monitoring of peatlands, a crucial aspect not fully addressed when relying solely on hyperspectral imaging or airborne and UAV data for peatland monitoring (Figure 4).

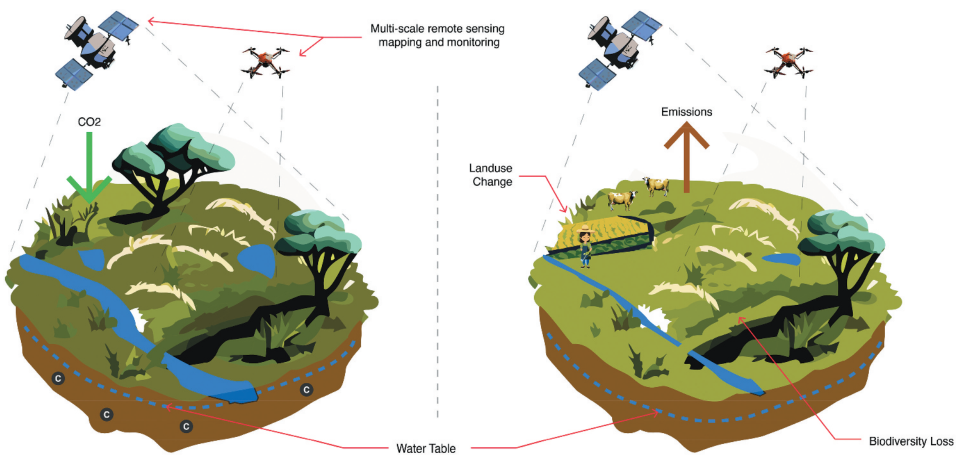

Figure 4. Multi-scale framework of peatland mapping and monitoring with remote sensing based datasets supporting the assessment of biodiversity, water table depth, and emission in peatlands with different conditions.

4.1. Challenges and opportunities

Ground validation is one of the main challenges of remote sensing based peatland mapping and monitoring, as it is crucial that observations align with actual on-site conditions (Lees et al. 2018). Especially in heterogeneous landscapes, the task of integrating field-collected data with remote sensing image pixels is challenging and a significant portion of the uncertainty in models that utilize remote sensing for large-area mapping is rooted in the integration of field data (Leitão et al. 2018). Especially in the case of satellite data use, there are limitations in capturing fine-scale biodiversity patterns (Harris and Bryant 2009; Krankina et al. 2008) as often it was shown that spatial variability in species composition (both vascular and mosses) in peatlands can be observed at small spatial scales (<1 m) (Kalacska, Lalonde and Moore 2015).

For example, in some cases, radar satellite data alone might be too coarse for monitoring peatlands as these ecosystems might exhibit a high degree of sub-pixel heterogeneity in vegetation composition and microtopography (Sadeghi et al. 2017; Toca et al. 2023). The spatial scale might be a factor in why some studies found that there is no 'one-size-fits-all approach' for deriving WTD in peatlands (Räsänen, Tolvanen and Kareksela 2022; Toca et al. 2023). Also, Burdun, Bechtold, Sagris, Lohila, et al. (2020) found the quality of OPTRAM results to be highly dependent on the spatial resolution of the data used. In the case of WTD, integration of thermal data has been shown beneficial (Burdun, Sagris and Mander 2019). Other challenges, such as cloud cover and sensor calibration, can further decrease the amount of available imagery for analysis. For this, the integrated use of multisource data can be a solution as shown in the case of the use of PlanetScope and Sentinel data, as well as synergistic use of SAR and optical data (Figure 4).

4.2. Future prospects

Expanding the presented research directions, future monitoring efforts could focus on improving the spatial and temporal resolution of data by integrating them from various sources. This integration aims to detect subtle and rapid changes in peatland ecosystems.

Another approach can be cross-scale assessment and improvement of upscaling possibilities. Some attempts have been made for PFT and microforms mapping with UAV data. They found that spatial vegetation characteristics significantly influence the minimum spatial resolution required for accurately capturing microforms. For PFTs, a resolution of at least 0.25 m is necessary (Steenvoorden and Limpens 2023). Other upscaling approaches have been tested for GPP assessment ecosystem respiration based on Sentinel-2 and MODIS data (Junttila et al. 2021) and UAV data (Kelly et al. 2021), using PlanetScope data for methane flux upscaling (Ingle et al. 2023) or for mapping near-surface moisture using data from laboratory, field and airborne imagery (Harris and Bryant 2009). However, additional multi-scale assessments can improve these methodologies. Further advancements in multi-scale assessment could involve the integration of UAV-derived high-resolution data with satellite imagery to bridge the gap between local- and regional-scale observations. Alternatively, UAV data can also be used to validate the large area output generated based on satellite data, such as nested approaches shown based on UAV and Sentinel-2 data (Bhatnagar et al. 2021). This synergy could significantly enhance our understanding of peatland dynamics, especially in the context of climate change. The application of advanced sensor technologies such as hyperspectral imaging, LiDAR and radar can yield a more comprehensive analysis of peatland characteristics. For example, combining 30 m resolution hyperspectral data (e.g. PRISMA, EnMAP) with the temporally denser Sentinel-2 time series, which offers 10 m resolution, presents a promising avenue for detailed monitoring (Arasumani et al. 2023). This created the baseline for further use of data coming from future missions such as CHIME (Copernicus Hyperspectral Imaging Mission for the Environment) and HyspIRI/SBG (Surface Biology and Geology) for more operational assessment.

Extended remote sensing research over time is crucial for evaluating the success of restoration methods in peatlands and for gaining insights into the recuperation of these environments. Although advancements have been made in this field, there remains a significant lack of documented studies from locations that have experienced restoration efforts. The potential for such studies based on Sentinel-2 has already been demonstrated, as evidenced by Ball et al. (2023).

Many peatland processes, such as SOC dynamics and the effects of restoration, unfold over extended periods, often spanning 30–50 years. Remote sensing alone may not suffice to capture the full scope of these long-term processes. Process-based models can aid in scenario-based analysis, offering predictions and insights into future peatland conditions under varying environmental and management scenarios (Mozafari et al. 2023) as well as improved estimations of different variables (Bechtold et al. 2020). Dynamic feedbacks between plant growth and soil organic carbon are modelled in the described models (Basso et al. 2018). Such relationships must be explicitly taken into account when soils are not in equilibrium due to climatic conditions or land use changes.

5. Conclusion

The review underscores the increasing significance and application of remote sensing in the mapping and monitoring of peatlands. Specifically, it centred on the assessment of vegetation and biodiversity, where the application of hyperspectral and multispectral sensors was emphasized as a promising strategy for cross-scale analysis. There was a notable increase in the utilization of remote sensing methodologies, primarily driven by the increased availability of datasets such as Sentinel 1 and 2 and the adoption of hyperspectral sensors. The statistical breakdown revealed a predominant focus on satellite-based remote sensing data, with a smaller number of studies using airborne and UAV data. The criticality of multi-temporal acquisition and the essential role of seasonality in such assessments were highlighted. For Water Table Depth assessment, the integrated use of optical and Synthetic Aperture Radar technologies was emphasized. Additionally, the review brought to light recently emerging methods for evaluating peatland restoration and the potential for Soil Organic Carbon mapping based on above-ground vegetation properties. However, challenges remain, particularly in ground validation and integrating field data with remote sensing observations. The review points to the necessity of integration of multisource data and for cross-scale assessments, which can bridge the gap between local and regional observations. Moving forward, further research should concentrate on the integration of process-based modelling for comprehensive long-term assessment.

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References

Akumu, C. E., and J. W. McLaughlin. 2014. "Modeling Peatland Carbon Stock in a Delineated Portion of the Nayshkootayaow River Watershed in Far North, Ontario Using an Integrated GIS and Remote Sensing Approach." *Catena* 121:297–306. https://doi.org/10.1016/j.catena.2014.05.025.

Antala, M., R. Juszczak, C. van der Tol, and A. Rastogi. 2022. "Impact of Climate Change-Induced Alterations in Peatland Vegetation Phenology and Composition on Carbon Balance." *Science of the Total Environment* 827:154294. https://doi.org/10.1016/j.scitotenv.2022.154294.

Arasumani, M., F. Thiel, V.-D. Pham, C. Hellmann, M. Kaiser, and S. van der Linden. 2023. "Advancing Peatland Vegetation Mapping by Spaceborne Imaging Spectroscopy." *Ecological Indicators* 154:110665. https://doi.org/10.1016/j.ecolind.2023.110665.

Arroyo-Mora, J. P., M. Kalacska, R. Soffer, G. Ifimov, G. Leblanc, E. S. Schaaf, and O. Lucanus. 2018. "Evaluation of Phenospectral Dynamics with Sentinel-2A Using a Bottom-Up Approach in a Northern Ombrotrophic Peatland." *Remote Sensing of Environment* 216:544–560. https://doi.org/10.1016/j.rse.2018.07.021.

Arroyo-Mora, J. P., M. Kalacska, R. J. Soffer, T. R. Moore, N. T. Roulet, S. Juutinen, G. Ifimov, G. Leblanc, and D. Inamdar. 2018. "Airborne Hyperspectral Evaluation of Maximum Gross Photosynthesis, Gravimetric Water Content, and CO2 Uptake Efficiency of the Mer Bleue Ombrotrophic Peatland." *Remote Sensing* 10 (4): 565. https://doi.org/10.3390/rs10040565.

Artz, R. R. E., S. Johnson, P. Bruneau, A. J. Britton, R. J. Mitchell, L. Ross, G. Donaldson-Selby, et al. 2019. "The Potential for Modelling Peatland Habitat Condition in Scotland Using Long-Term MODIS Data." *Science of the Total Environment* 660:429–442. https://doi.org/10.1016/j.scitotenv.2018.12.327.

Asmuß, T., M. Bechtold, and B. Tiemeyer. 2019. "On the Potential of Sentinel-1 for High Resolution Monitoring of Water Table Dynamics in Grasslands on Organic Soils." *Remote Sensing* 11 (14): 1659. https://doi.org/10.3390/rs11141659.

Assiri, M., A. Sartori, A. Persichetti, C. Miele, R. A. Faelga, T. Blount, and S. Silvestri. 2023. "Leaf Area Index and Aboveground Biomass Estimation of an Alpine Peatland with a UAV Multi-Sensor Approach." *GIScience & Remote Sensing* 60 (1): 2270791. https://doi.org/10.1080/15481603.2023.2270791.

Babaeian, E., M. Sadeghi, S. B. Jones, C. Montzka, H. Vereecken, and M. Tuller. 2019. "Ground, Proximal, and Satellite Remote Sensing of Soil Moisture." *Reviews of Geophysics* 57 (2): 530–616. https://doi.org/10.1029/2018RG000618.

Ball, J., A. Gimona, N. Cowie, M. Hancock, D. Klein, G. Donaldson-Selby, and R. R. E. Artz. 2023. "Assessing the Potential of Using Sentinel-1 and 2 or High-Resolution Aerial Imagery Data with Machine Learning and Data Science Techniques to Model Peatland Restoration Progress – a Northern Scotland Case Study." *International Journal of Remote Sensing* 44 (9): 2885–2911. https://doi.org/10.1080/01431161.2023.2209916.

Basso, B., B. Dumont, B. Maestrini, I. Shcherbak, G. P. Robertson, J. R. Porter, P. Smith, et al. 2018. "Soil Organic Carbon and Nitrogen Feedbacks on Crop Yields Under Climate Change." *Agricultural & Environmental Letters* 3 (1): 180026. https://doi.org/10.2134/ael2018.05.0026.

Bechtold, M., G. J. M. De Lannoy, R. H. Reichle, D. Roose, N. Balliston, I. Burdun, K. Devito, J. Kurbatova, M. Strack, and E. A. Zarov. 2020. "Improved Groundwater Table and L-Band Brightness Temperature Estimates for Northern Hemisphere Peatlands Using New Model Physics and SMOS Observations in a Global Data Assimilation Framework." *Remote Sensing of Environment* 246:111805. https://doi.org/10.1016/j.rse.2020.111805.

Bechtold, M., S. Schlaffer, B. Tiemeyer, and G. De Lannoy. 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): 536. https://doi.org/10.3390/rs10040536.

Bechtold, M., B. Tiemeyer, A. Laggner, T. Leppelt, E. Frahm, and S. Belting. 2014. "Large-Scale Regionalization of Water Table Depth in Peatlands Optimized for Greenhouse Gas Emission Upscaling." *Hydrology and Earth System Sciences* 18 (9): 3319–3339. https://doi.org/10.5194/hess-18-3319-2014.

Beyer, F., G. Jurasinski, J. Couwenberg, and G. Grenzdörffer. 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., L. Gill, S. Regan, S. Waldren, and B. Ghosh. 2021. "A Nested Drone-Satellite Approach to Monitoring the Ecological Conditions of Wetlands." *Isprs Journal of Photogrammetry & Remote Sensing* 174:151–165. https://doi.org/10.1016/j.isprsjprs.2021.01.012.

Bhullar, G. S., M. Iravani, P. J. Edwards, and H. Olde Venterink. 2013. "Methane Transport and Emissions from Soil as Affected by Water Table and Vascular Plants." *BMC ecology* 13 (1): 32. https://doi.org/10.1186/1472-6785-13-32.

Bourgeau-Chavez, L. L., S. Endres, R. Powell, M. J. Battaglia, B. Benscoter, M. Turetsky, E. S. Kasischke, and E. Banda. 2017. "Mapping Boreal Peatland Ecosystem Types from Multitemporal Radar and Optical Satellite Imagery." *Canadian Journal of Forest Research* 47 (4): 545–559. https://doi.org/10.1139/cjfr-2016-0192.

Bourgeau-Chavez, L. L., S. L. Grelik, M. J. Battaglia, D. J. Leisman, R. A. Chimner, J. A. Hribljan, E. A. Lilleskov, et al. 2021. "Advances in Amazonian Peatland Discrimination with Multi-Temporal PALSAR Refines Estimates of Peatland Distribution, C Stocks and Deforestation." *Frontiers in Earth Science* 9. https://doi.org/10.3389/feart.2021.676748.

Bryant, R. G., and A. J. Baird. 2003. "The Spectral Behaviour of Sphagnum Canopies Under Varying Hydrological Conditions." *Geophysical Research Letters* 30 (3): 30. https://doi.org/10.1029/2002GL016053.

Bubier, J. L., B. N. Rock, and P. M. Crill. 1997. "Spectral Reflectance Measurements of Boreal Wetland and Forest Mosses." *Journal of Geophysical Research Atmospheres* 102 (D24): 29483–29494. https://doi.org/10.1029/97JD02316.

Burdun, I., M. Bechtold, M. Aurela, G. De Lannoy, A. R. Desai, E. Humphreys, S. Kareksela, et al. 2023. "Hidden Becomes Clear: Optical Remote Sensing of Vegetation Reveals Water Table Dynamics in Northern Peatlands." *Remote Sensing of Environment* 296:113736. https://doi.org/10.1016/j.rse.2023.113736.

Burdun, I., M. Bechtold, V. Sagris, V. Komisarenko, G. De Lannoy, and Ü. Mander. 2020. "A Comparison of Three Trapezoid Models Using Optical and Thermal Satellite Imagery for Water Table Depth Monitoring in Estonian Bogs." *Remote Sensing* 12:1980. https://doi.org/10.3390/rs12121980.

Burdun, I., M. Bechtold, V. Sagris, A. Lohila, E. Humphreys, A. R. Desai, M. B. Nilsson, G. De Lannoy, and Ü. Mander. 2020. "Satellite Determination of Peatland Water Table Temporal Dynamics by Localizing Representative Pixels of a SWIR-Based Moisture Index." *Remote Sensing* 12 (18): 2936. https://doi.org/10.3390/rs12182936.

Burdun, I., A. Kull, M. Maddison, G. Veber, O. Karasov, V. Sagris, and Ü. Mander. 2021. "Remotely Sensed Land Surface Temperature Can Be Used to Estimate Ecosystem Respiration in Intact and Disturbed Northern Peatlands." *Journal of Geophysical Research: Biogeosciences* 126 (11): e2021JG006411. https://doi.org/10.1029/2021JG006411.

Burdun, I., V. Sagris, and Ü. Mander. 2019. "Relationships Between Field-Measured Hydrometeorological Variables and Satellite-Based Land Surface Temperature in a Hemiboreal Raised Bog." *International Journal of Applied Earth Observation and Geoinformation* 74:295–301. https://doi.org/10.1016/j.jag.2018.09.019.

Cabezas, J., M. Galleguillos, A. Valdés, J. P. Fuentes, C. Pérez, and J. F. Perez-Quezada. 2015. "Evaluation of Impacts of Management in an Anthropogenic Peatland Using Field and Remote Sensing Data." *Ecosphere* 6 (12): 1–24. https://doi.org/10.1890/ES15-00232.1.

Castaldi, F., A. Hueni, S. Chabrillat, K. Ward, G. Buttafuoco, B. Bomans, K. Vreys, M. Brell, and B. van Wesemael. 2019. "Evaluating the Capability of the Sentinel 2 Data for Soil Organic Carbon Prediction in Croplands." *Isprs Journal of Photogrammetry & Remote Sensing* 147:267–282. https://doi.org/10.1016/j.isprsjprs.2018.11.026.

Cherukuru, N., P. Martin, N. Sanwlani, A. Mujahid, and M. Müller. 2021. "A Semi-Analytical Optical Remote Sensing Model to Estimate Suspended Sediment and Dissolved Organic Carbon in Tropical Coastal Waters Influenced by Peatland-Draining River Discharges off Sarawak, Borneo." *Remote Sensing* 13 (1): 99. https://doi.org/10.3390/rs13010099.

Cole, B., J. McMorrow, and M. Evans. 2014. “Spectral Monitoring of Moorland Plant Phenology to Identify a Temporal Window for Hyperspectral Remote Sensing of Peatland.” *Isprs Journal of Photogrammetry & Remote Sensing* 90:49–58. https://doi.org/10.1016/j.isprsjprs.2014.01.010.
Connolly, J., N. M. Holden, J. Connolly, J. W. Seaquist, and S. M. Ward. 2011. “Detecting Recent Disturbance on Montane Blanket Bogs in the Wicklow Mountains, Ireland Using the MODIS Enhanced Vegetation Index.” *International Journal of Remote Sensing* 32 (9): 2377–2393. https://doi.org/10.1080/01431161003698310.
Crezee, B., G. C. Dargie, C. E. Ewango, E. T. A. Mitchard, B. O. Emba, T. J. Kanyama, P. Bola, et al. 2022. “Mapping Peat Thickness and Carbon Stocks of the Central Congo Basin Using Field Data.” *Nature Geoscience* 15 (8): 639–644. https://doi.org/10.1038/s41561-022-00966-7.
Crichton, K. A., K. Anderson, J. J. Bennie, and E. J. Milton. 2015. “Characterizing Peatland Carbon Balance Estimates Using Freely Available Landsat ETM+ Data.” *Ecohydrology* 8 (3): 493–503. https://doi.org/10.1002/eco.1519.
Czapiewski, S., and D. Szumińska. 2022. “An Overview of Remote Sensing Data Applications in Peatland Research Based on Works from the Period 2010–2021.” *The Land* 11 (1): 24. https://doi.org/10.3390/land11010024.
Dabrowska-Zielinska, K., J. Musial, A. Malinska, M. Budzynska, R. Gurdak, W. Kiryla, M. Bartold, and P. Grzybowski. 2018. “Soil Moisture in the Biebrza Wetlands Retrieved from Sentinel-1 Imagery.” *Remote Sensing* 10 (12): 1979. https://doi.org/10.3390/rs10121979.
de Sousa Mendes, W., M. Sommer, S. Koszinski, and M. Wehrhan. 2023. “The Power of Integrating Proximal and High-Resolution Remote Sensing for Mapping SOC Stocks in Agricultural Peatlands.” *Plant and Soil* 492 (1–2): 501–517. https://doi.org/10.1007/s11104-023-06198-x.
Dettmann, U., and M. Bechtold. 2016. “Deriving Effective Soil Water Retention Characteristics from Shallow Water Table Fluctuations in Peatlands.” *Vadose Zone Journal* 15 (10): 1–13. https://doi.org/10.2136/vzj2016.04.0029.
Dieleman, C. M., B. A. Branfireun, J. W. McLaughlin, and Z. Lindo. 2015. “Climate Change Drives a Shift in Peatland Ecosystem Plant Community: Implications for Ecosystem Function and Stability.” *Global Change Biology* 21 (1): 388–395.
Erudel, T., S. Fabre, T. Houet, F. Mazier, and X. Briottet. 2017. “Criteria Comparison for Classifying Peatland Vegetation Types Using in situ Hyperspectral Measurements.” *Remote Sensing* 9 (7): 748. https://doi.org/10.3390/rs9070748.
Evans, C. D., M. Peacock, A. J. Baird, R. R. E. Artz, A. Burden, N. Callaghan, P. J. Chapman, et al. 2021. “Overriding Water Table Control on Managed Peatland Greenhouse Gas Emissions.” *Nature* 593 (7860): 548–552. https://doi.org/10.1038/s41586-021-03523-1.
FAO. 2020. *Peatland Mapping and Monitoring: Recommendations and Technical Overview*. Rome, Italy: FAO. https://doi.org/10.4060/ca8200en.
Fiantis, D., F. I. Rudiyanto Ginting, A. Agtalarik, D. T. Arianto, P. Wichaksono, R. Irfan, M. Nelson, et al. 2024. “Mapping Peat Thickness and Carbon Stock of a Degraded Peatland in West Sumatra, Indonesia.” *Soil Use and Management* 40 (1): e12954. https://doi.org/10.1111/sum.12954.
Franke, J., V. Keuck, and F. Siegert. 2012. “Assessment of Grassland Use Intensity by Remote Sensing to Support Conservation Schemes.” *Journal for Nature Conservation* 20 (3): 125–134. https://doi.org/10.1016/j.jnc.2012.02.001.
Frick, A., P. Steffenhagen, S. Zerbe, T. Timmermann, and K. Schulz. 2011. “Monitoring der Vegetationszusammensetzung in wiedervernässten Niedermooren anhand einer iterativen decision tree Klassi kation von Satellitendaten.” *Photogrammetrie - Fernerkundung - Geoinformation* 2011 (3): 109–122. https://doi.org/10.1127/1432-8364/2011/0076.
Garisoain, R., C. Delire, B. Decharme, S. Ferrant, F. Granouillac, V. Payre-Suc, and L. Gandois. 2023. “A Study of Dominant Vegetation Phenology in a Sphagnum Mountain Peatland Using in situ and Sentinel-2 Observations.” *Journal of Geophysical Research: Biogeosciences* 128 (10): e2023JG007403. https://doi.org/10.1029/2023JG007403.
Gholizadeh, A., C. Neumann, S. Chabrillat, B. van Wesemael, F. Castaldi, L. Borůvka, J. Sanderman, A. Klement, and C. Hohmann. 2021. “Soil Organic Carbon Estimation Using VNIR–SWIR Spectroscopy: The Effect of Multiple Sensors and Scanning Conditions.” *Soil and Tillage Research* 211:105017. https://doi.org/10.1016/j.still.2021.105017.

Greifswald Mire Centre. 2022. "Global Peatland Map 2.0. Underlying dataset of the Global Peatlands Assessment - The State of the World's Peatlands: Evidence for action toward the conservation, restoration, and sustainable management of peatlands." *Global Peatlands Initiative*. Nairobi: United Nations Environment Programme.

Greifswald Mire Centre (GMC). 2015. "Global Peatland Database." Accessed December 20, 2023. https://greifswaldmoor.de/global-peatland-database-en.html.

Harris, A., and R. G. Bryant. 2009. "A Multi-Scale Remote Sensing Approach for Monitoring Northern Peatland Hydrology: Present Possibilities and Future Challenges." *The Journal of Environmental Management* 90 (7): 2178–2188. https://doi.org/10.1016/j.jenvman.2007.06.025.

Harris, A., R. Charnock, and R. M. Lucas. 2015. "Hyperspectral Remote Sensing of Peatland Floristic Gradients." *Remote Sensing of Environment* 162:99–111. https://doi.org/10.1016/j.rse.2015.01.029.

Hilbert, D. W., N. Roulet, and T. Moore. 2000. "Modelling and Analysis of Peatlands as Dynamical Systems." *The Journal of Ecology* 88 (2): 230–242. https://doi.org/10.1046/j.1365-2745.2000.00438.x.

Hribljan, J. A., E. Suarez, L. Bourgeau-Chavez, S. Endres, E. A. Lilleskov, S. Chimbolema, C. Wayson, E. Serocki, and R. A. Chimner. 2017. "Multidate, Multisensor Remote Sensing Reveals High Density of Carbon-Rich Mountain Peatlands in the páramo of Ecuador." *Global Change Biology* 23 (12): 5412–5425. https://doi.org/10.1111/gcb.13807.

Ikkala, L., A.-K. Ronkanen, O. Utriainen, B. Kløve, and H. Marttila. 2021. "Peatland Subsidence Enhances Cultivated Lowland Flood Risk." *Soil and Tillage Research* 212:105078. https://doi.org/10.1016/j.still.2021.105078.

Ingle, R., W. Habib, J. Connolly, M. McCorry, S. Barry, and M. Saunders. 2023. "Upscaling Methane Fluxes from Peatlands Across a Drainage Gradient in Ireland Using PlanetScope Imagery and Machine Learning Tools." *Scientific Reports* 13 (1): 11997. https://doi.org/10.1038/s41598-023-38470-6.

Isoaho, A., L. Ikkala, H. Marttila, J. Hjort, T. Kumpula, P. Korpelainen, and A. Räsänen. 2023. "Spatial Water Table Level Modelling with Multi-Sensor Unmanned Aerial Vehicle Data in Boreal Aapa Mires." *Remote Sensing Applications: Society & Environment* 32:101059. https://doi.org/10.1016/j.rsase.2023.101059.

Jackson, R. B., K. Lajtha, S. E. Crow, G. Hugelius, M. G. Kramer, and G. Piñeiro. 2017. "The Ecology of Soil Carbon: Pools, Vulnerabilities, and Biotic and Abiotic Controls." *Annual Review of Ecology, Evolution, and Systematics* 48 (1): 419–445. https://doi.org/10.1146/annurev-ecolsys-112414-054234.

Joosten, H., and D. Clarke. 2002. *Wise Use of Mires and Peatlands: Background and Principles Including a Framework for Decision-Making*. Devon, UK: International Peat Society ; International Mire Conservation Group.

Junttila, S., J. Kelly, N. Kljun, M. Aurela, L. Klemedtsson, A. Lohila, M. B. Nilsson, et al. 2021. "Upscaling Northern Peatland CO2 Fluxes Using Satellite Remote Sensing Data." *Remote Sensing* 13 (4): 818. https://doi.org/10.3390/rs13040818.

Kalacska, M., J. P. Arroyo-Mora, R. J. Soffer, N. T. Roulet, T. R. Moore, E. Humphreys, G. Leblanc, O. Lucanus, and D. Inamdar. 2018. "Estimating Peatland Water Table Depth and Net Ecosystem Exchange: A Comparison Between Satellite and Airborne Imagery." *Remote Sensing* 10 (5): 687. https://doi.org/10.3390/rs10050687.

Kalacska, M., M. Lalonde, and T. R. Moore. 2015. "Estimation of Foliar Chlorophyll and Nitrogen Content in an Ombrotrophic Bog from Hyperspectral Data: Scaling from Leaf to Image." *Remote Sensing of Environment* 169:270–279. https://doi.org/10.1016/j.rse.2015.08.012.

Kameoka, T., O. Kozan, S. Hadi, and H. Asnawi. 2021. "Monitoring the Groundwater Level in Tropical Peatland Through UAV Mapping of Soil Surface Temperature: A Pilot Study in Tanjung Leban, Indonesia." *Remote Sensing Letters* 12 (6): 542–552. https://doi.org/10.1080/2150704X.2021.1906974.

Karlson, M., M. Gålfalk, P. Crill, P. Bousquet, M. Saunois, and D. Bastviken. 2019. "Delineating Northern Peatlands Using Sentinel-1 Time Series and Terrain Indices from Local and Regional Digital Elevation Models." *Remote Sensing of Environment* 231:111252. https://doi.org/10.1016/j.rse.2019.111252.

Kattenborn, T., F. E. Fassnacht, S. Pierce, J. Lopatin, J. P. Grime, S. Schmidtlein, and J. Paruelo. 2017. "Linking Plant Strategies and Plant Traits Derived by Radiative Transfer Modelling." *Journal of Vegetation Science* 28 (4): 717–727. https://doi.org/10.1111/jvs.12525.

Kelly, J., N. Kljun, L. Eklundh, L. Klemedtsson, B. Liljebladh, P.-O. Olsson, P. Weslien, and X. Xie. 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* 300:108330. https://doi.org/10.1016/j.agrformet.2021.108330.

Knoth, C., B. Klein, T. Prinz, T. Kleinebecker, and S. Goslee. 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.

Krankina, O. N., D. Pflugmacher, M. Friedl, W. B. Cohen, P. Nelson, and A. Baccini. 2008. "Meeting the Challenge of Mapping Peatlands with Remotely Sensed Data." *Biogeosciences* 5 (6): 1809–1820. https://doi.org/10.5194/bg-5-1809-2008.

Kreyling, J., F. Tanneberger, F. Jansen, S. Van Der Linden, C. Aggenbach, V. Blüml, J. Couwenberg, et al. 2021. "Rewetting Does Not Return Drained Fen Peatlands to Their Old Selves." *Nature Communications* 12 (1): 5693. https://doi.org/10.1038/s41467-021-25619-y.

Kross, A., J. W. Seaquist, N. T. Roulet, R. Fernandes, and O. Sonnentag. 2013. "Estimating Carbon Dioxide Exchange Rates at Contrasting Northern Peatlands Using MODIS Satellite Data." *Remote Sensing of Environment* 137:234–243. https://doi.org/10.1016/j.rse.2013.06.014.

Lamichhane, S., L. Kumar, and B. Wilson. 2019. "Digital Soil Mapping Algorithms and Covariates for Soil Organic Carbon Mapping and Their Implications: A Review." *Geoderma* 352: 395–413. https://doi.org/10.1016/j.geoderma.2019.05.031 .

Lees, K. J., R. R. E. Artz, D. Chandler, T. Aspinall, C. A. Boulton, J. Buxton, N. R. Cowie, and T. M. Lenton. 2021. "Using Remote Sensing to Assess Peatland Resilience by Estimating Soil Surface Moisture and Drought Recovery." *Science of the Total Environment* 761:143312. https://doi.org/10.1016/j.scitotenv.2020.143312.

Lees, K. J., M. Khomik, T. Quaife, J. M. Clark, T. Hill, D. Klein, J. Ritson, and R. R. E. Artz. 2021. "Assessing the Reliability of Peatland GPP Measurements by Remote Sensing: From Plot to Landscape Scale." *Science of the Total Environment* 766:142613. https://doi.org/10.1016/j.scitotenv.2020.142613.

Lees, K. J., T. Quaife, R. R. E. Artz, M. Khomik, and J. M. Clark. 2018. "Potential for Using Remote Sensing to Estimate Carbon Fluxes Across Northern Peatlands – a Review." *Science of the Total Environment* 615:857–874. https://doi.org/10.1016/j.scitotenv.2017.09.103.

Lehmann, J. R. K., W. Münchberger, C. Knoth, C. Blodau, F. Nieberding, T. Prinz, V. A. Pancotto, and T. Kleinebecker. 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.

Leifeld, J., and L. Menichetti. 2018. "The Underappreciated Potential of Peatlands in Global Climate Change Mitigation Strategies." *Nature Communications* 9 (1): 1071. https://doi.org/10.1038/s41467-018-03406-6.

Leitão, P. J., M. Schwieder, F. Pötzschner, J. R. R. Pinto, A. M. C. Teixeira, F. Pedroni, M. Sanchez, et al. 2018. "From Sample to Pixel: Multi-Scale Remote Sensing Data for Upscaling Aboveground Carbon Data in Heterogeneous Landscapes." *Ecosphere* 9:e02298. https://doi.org/10.1002/ecs2.2298.

Li, Z.-L., P. Leng, C. Zhou, K.-S. Chen, F.-C. Zhou, and G.-F. Shang. 2021. "Soil Moisture Retrieval from Remote Sensing Measurements: Current Knowledge and Directions for the Future." *Earth-Science Reviews* 218:103673. https://doi.org/10.1016/j.earscirev.2021.103673.

Limpens, J., F. Berendse, C. Blodau, J. G. Canadell, C. Freeman, J. Holden, N. Roulet, H. Rydin, and G. Schaepman-Strub. 2008. "Peatlands and the Carbon Cycle: From Local Processes to Global Implications – a Synthesis." *Biogeosciences* 5: 1475–1491. https://doi.org/10.5194/bg-5-1475-2008.

Loisel, J., A. V. Gallego-Sala, M. J. Amesbury, G. Magnan, G. Anshari, D. W. Beilman, J. C. Benavides, et al. 2021. "Expert Assessment of Future Vulnerability of the Global Peatland Carbon Sink." *Nature Climate Change* 11 (1): 70–77. https://doi.org/10.1038/s41558-020-00944-0.

Lopatin, J., T. Kattenborn, M. Galleguillos, J. Perez-Quezada, and S. Schmidtlein. 2019. "Using Aboveground Vegetation Attributes as Proxies for Mapping Peatland Belowground Carbon Stocks." *Remote Sensing of Environment* 231:111217. https://doi.org/10.1016/j.rse.2019.111217.

Lourenco, M., J. M. Fitchett, and S. Woodborne. 2023. "Peat Definitions: A Critical Review." *Progress in Physical Geography: Earth and Environment* 47 (4): 506–520. https://doi.org/10.1177/03091333221118353.

Mcmorrow, J. M., M. E. J. Cutler, M. G. Evans, and A. Al-Roichdi. 2004. "Hyperspectral Indices for Characterizing Upland Peat Composition." *International Journal of Remote Sensing* 25 (2): 313–325. https://doi.org/10.1080/0143116031000117065.

McPartland, M. Y., M. J. Falkowski, J. R. Reinhardt, E. S. Kane, R. Kolka, M. R. Turetsky, T. A. Douglas, et al. 2019. "Characterizing Boreal Peatland Plant Composition and Species Diversity with Hyperspectral Remote Sensing." *Remote Sensing* 11:1685. https://doi.org/10.3390/rs11141685.

Mendes, W. D. S., and M. Sommer. 2023. "Advancing Soil Organic Carbon and Total Nitrogen Modelling in Peatlands: The Impact of Environmental Variable Resolution and Vis-NIR Spectroscopy Integration." *Agronomy* 13 (7): 1800. https://doi.org/10.3390/agronomy13071800.

Mendes, W. D. S., M. Sommer, S. Koszinski, and M. Wehrhan. 2022. "Peatlands Spectral Data Influence in Global Spectral Modelling of Soil Organic Carbon and Total Nitrogen Using Visible-Near-Infrared Spectroscopy." *The Journal of Environmental Management* 317:115383. https://doi.org/10.1016/j.jenvman.2022.115383.

Merchant, M. A., J. R. Adams, A. A. Berg, J. L. Baltzer, W. L. Quinton, and L. E. Chasmer. 2017. "Contributions of C-Band SAR Data and Polarimetric Decompositions to Subarctic Boreal Peatland Mapping." *IEEE Journal of Selected Topics in Applied Earth Observations & Remote Sensing* 10 (4): 1467–1482. https://doi.org/10.1109/JSTARS.2016.2621043.

Middleton, M., P. Närhi, H. Arkimaa, E. Hyvönen, V. Kuosmanen, P. Treitz, and R. Sutinen. 2012. "Ordination and Hyperspectral Remote Sensing Approach to Classify Peatland Biotopes Along Soil Moisture and Fertility Gradients." *Remote Sensing of Environment* 124:596–609. https://doi.org/10.1016/j.rse.2012.06.010.

Millard, K., P. Kirby, S. Nandlall, A. Behnamian, S. Banks, and F. Pacini. 2020. "Using Growing-Season Time Series Coherence for Improved Peatland Mapping: Comparing the Contributions of Sentinel-1 and RADARSAT-2 Coherence in Full and Partial Time Series." *Remote Sensing* 12 (15): 2465. https://doi.org/10.3390/rs12152465.

Minasny, B., D. V. Adetsu, M. Aitkenhead, R. R. E. Artz, N. Baggaley, A. Barthelmes, A. Beucher, et al. 2023. "Mapping and Monitoring Peatland Conditions from Global to Field Scale." *Biogeochemistry* 167 (4): 383–425. https://doi.org/10.1007/s10533-023-01084-1.

Minasny, B., Ö. Berglund, J. Connolly, C. Hedley, F. de Vries, A. Gimona, B. Kempen, et al. 2019. "Digital Mapping of Peatlands – a Critical Review." *Earth-Science Reviews* 196:102870. https://doi.org/10.1016/j.earscirev.2019.05.014.

Minayeva, T. Y., O. Bragg, and A. A. Sirin. 2017. "Towards Ecosystem-Based Restoration of Peatland Biodiversity." *Mires Peat* 19 (1): 1–36.

Montanarella, L., R. J. Jones, and R. Hiederer. 2006. "The Distribution of Peatland in Europe." *Mires Peat* 1:1–10.

Monteverde, S., M. G. Healy, D. O'Leary, E. Daly, and O. Callery. 2022. "Management and Rehabilitation of Peatlands: The Role of Water Chemistry, Hydrology, Policy, and Emerging Monitoring Methods to Ensure Informed Decision Making." *Ecological Informatics* 69:101638. https://doi.org/10.1016/j.ecoinf.2022.101638.

Mozafari, B., M. Bruen, S. Donohue, F. Renou-Wilson, and F. O'Loughlin. 2023. "Peatland Dynamics: A Review of Process-Based Models and Approaches." *Science of the Total Environment* 877:162890. https://doi.org/10.1016/j.scitotenv.2023.162890.

Nordbeck, R., and K. Hogl. 2023. "National Peatland Strategies in Europe: Current Status, Key Themes, and Challenges." *Regional Environmental Change* 24 (1): 5. https://doi.org/10.1007/s10113-023-02166-4.

Odebiri, O., O. Mutanga, J. Odindi, and R. Naicker. 2023. "Mapping Soil Organic Carbon Distribution Across South Africa's Major Biomes Using Remote Sensing-Topo-Climatic Covariates and

Concrete Autoencoder-Deep Neural Networks." *Science of the Total Environment* 865:161150. https://doi.org/10.1016/j.scitotenv.2022.161150.

Odebiri, O., J. Odindi, and O. Mutanga. 2021. "Basic and Deep Learning Models in Remote Sensing of Soil Organic Carbon Estimation: A Brief Review." *International Journal of Applied Earth Observation and Geoinformation* 102:102389. https://doi.org/10.1016/j.jag.2021.102389.

Pang, Y., A. Räsänen, V. Lindholm, M. Aurela, and T. Virtanen. 2022. "Detecting Peatland Vegetation Patterns with Multi-Temporal Field Spectroscopy." *GIScience & Remote Sensing* 59 (1): 2111–2126. https://doi.org/10.1080/15481603.2022.2152303.

Park, H., W. Takeuchi, and K. Ichii. 2020. "Satellite-Based Estimation of Carbon Dioxide Budget in Tropical Peatland Ecosystems." *Remote Sensing* 12 (2): 250. https://doi.org/10.3390/rs12020250.

Parry, L. E., P. J. Chapman, S. M. Palmer, Z. E. Wallage, H. Wynne, and J. Holden. 2015. "The Influence of Slope and Peatland Vegetation Type on Riverine Dissolved Organic Carbon and Water Colour at Different Scales." *Science of the Total Environment* 527-528:530–539. https://doi.org/10.1016/j.scitotenv.2015.03.036.

Pflugmacher, D., O. N. Krankina, and W. B. Cohen. 2007. "Satellite-Based Peatland Mapping: Potential of the MODIS Sensor." *Global and Planetary Change* 56 (3–4): 248–257. https://doi.org/10.1016/j.gloplacha.2006.07.019.

Qiu, C., D. Zhu, P. Ciais, B. Guenet, S. Peng, and X. Xu. 2020. "The Role of Northern Peatlands in the Global Carbon Cycle for the 21st Century." *Global Ecology & Biogeography* 29 (5): 956–973. https://doi.org/10.1111/geb.13081.

Rahman, M. M., G. J. McDermid, M. Strack, and J. Lovitt. 2017. "A New Method to Map Groundwater Table in Peatlands Using Unmanned Aerial Vehicles." *Remote Sensing* 9 (10): 1057. https://doi.org/10.3390/rs9101057.

Räsänen, A., S. Juutinen, M. Kalacska, M. Aurela, P. Heikkinen, K. Mäenpää, A. Rimali, and T. Virtanen. 2020. "Peatland Leaf-Area Index and Biomass Estimation with Ultra-High Resolution Remote Sensing." *GIScience & Remote Sensing* 57 (7): 943–964. https://doi.org/10.1080/15481603.2020.1829377.

Räsänen, A., S. Juutinen, E.-S. Tuittila, M. Aurela, T. Virtanen, and D. Rocchini. 2019. "Comparing Ultra-High Spatial Resolution Remote-Sensing Methods in Mapping Peatland Vegetation." *Journal of Vegetation Science* 30 (5): 1016–1026. https://doi.org/10.1111/jvs.12769.

Räsänen, A., A. Tolvanen, and S. Kareksela. 2022. "Monitoring Peatland Water Table Depth with Optical and Radar Satellite Imagery." *International Journal of Applied Earth Observation and Geoinformation* 112:102866. https://doi.org/10.1016/j.jag.2022.102866.

Sadeghi, M., E. Babaeian, M. Tuller, and S. B. Jones. 2017. "The Optical Trapezoid Model: A Novel Approach to Remote Sensing of Soil Moisture Applied to Sentinel-2 and Landsat-8 Observations." *Remote Sensing of Environment* 198:52–68. https://doi.org/10.1016/j.rse.2017.05.041.

Schaepman-Strub, G., J. Limpens, M. Menken, H. M. Bartholomeus, and M. E. Schaepman. 2008. "Towards Spatial Assessment of Carbon Sequestration in Peatlands: Spectroscopy Based Estimation of Fractional Cover of Three Plant Functional Types." *Biogeosciences Discuss* 5 (2): 1293–1317.

Schmidtlein, S., H. Feilhauer, H. Bruelheide, and D. Rocchini. 2012. "Mapping Plant Strategy Types Using Remote Sensing." *Journal of Vegetation Science* 23 (3): 395–405. https://doi.org/10.1111/j.1654-1103.2011.01370.x.

Schubert, P., L. Eklundh, M. Lund, and M. Nilsson. 2010. "Estimating Northern Peatland CO2 Exchange from MODIS Time Series Data." *Remote Sensing of Environment* 114 (6): 1178–1189. https://doi.org/10.1016/j.rse.2010.01.005.

Steenvoorden, J., H. Bartholomeus, and J. Limpens. 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., and J. Limpens. 2023. "Upscaling Peatland Mapping with Drone-Derived Imagery: Impact of Spatial Resolution and Vegetation Characteristics." *GIScience & Remote Sensing* 60 (1): 2267851. https://doi.org/10.1080/15481603.2023.2267851.

Stuart, M. B., M. Davies, M. J. Hobbs, A. J. S. McGonigle, and J. R. Willmott. 2022. "Peatland Plant Spectral Response as a Proxy for Peat Health, Analysis Using Low-Cost Hyperspectral Imaging Techniques." *Remote Sensing* 14 (16): 3846. https://doi.org/10.3390/rs14163846.

Tanneberger, F., L. Appulo, S. Ewert, S. Lakner, N. Ó Brolcháin, J. Peters, and W. Wichtmann. 2021. "The Power of Nature-Based Solutions: How Peatlands Can Help Us to Achieve Key EU Sustainability Objectives." *Advanced Sustainable Systems* 5 (1): 2000146. https://doi.org/10.1002/adsu.202000146.

Thomas, V., P. Treitz, D. Jelinski, J. Miller, P. Lafleur, and J. H. McCaughey. 2003. "Image Classification of a Northern Peatland Complex Using Spectral and Plant Community Data." *Remote Sensing of Environment* 84 (1): 83–99. https://doi.org/10.1016/S0034-4257(02)00099-8.

Toca, L., R. R. E. Artz, C. Smart, T. Quaife, K. Morrison, A. Gimona, R. Hughes, M. H. Hancock, and D. Klein. 2023. "Potential for Peatland Water Table Depth Monitoring Using Sentinel-1 SAR Backscatter: Case Study of Forsinard Flows, Scotland, UK." *Remote Sensing* 15 (7): 1900. https://doi.org/10.3390/rs15071900.

Toca, L., K. Morrison, R. R. E. Artz, A. Gimona, and T. Quaife. 2022. "High Resolution C-Band SAR Backscatter Response to Peatland Water Table Depth and Soil Moisture: A Laboratory Experiment." *International Journal of Remote Sensing* 43 (14): 5231–5251. https://doi.org/10.1080/01431161.2022.2131478.

Torabi Haghighi, A., M. W. Menberu, H. Darabi, J. Akanegbu, and B. Kløve. 2018. "Use of Remote Sensing to Analyse Peatland Changes After Drainage for Peat Extraction." *Land Degradation & Development* 29 (10): 3479–3488. https://doi.org/10.1002/ldr.3122.

Tucker, C., A. O'Neill, K. Meingast, L. Bourgeau-Chavez, E. Lilleskov, and E. S. Kane. 2022. "Spectral Indices of Vegetation Condition and Soil Water Content Reflect Controls on CH4 and CO2 Exchange in Sphagnum-Dominated Northern Peatlands." *Journal of Geophysical Research: Biogeosciences* 127 (7): e2021JG006486. https://doi.org/10.1029/2021JG006486.

UNEP. 2022. Global Peatlands Assessment–The State of the world's Peatlands: Evidence for Action Toward the Conservation, Restoration, and Sustainable Management of Peatlands. Main Report. Global Peatlands Initiative.

Walker, T. N., M. H. Garnett, S. E. Ward, S. Oakley, R. D. Bardgett, and N. J. Ostle. 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.

White, L., K. Millard, S. Banks, M. Richardson, J. Pasher, and J. Duffe. 2017. "Moving to the RADARSAT Constellation Mission: Comparing Synthesized Compact Polarimetry and Dual Polarimetry Data with Fully Polarimetric RADARSAT-2 Data for Image Classification of Peatlands." *Remote Sensing* 9 (6): 573. https://doi.org/10.3390/rs9060573.

Zhou, Y., T. Sachs, Z. Li, Y. Pang, J. Xu, A. Kalhori, C. Wille, et al. 2023. "Long-Term Effects of Rewetting and Drought on GPP in a Temperate Peatland Based on Satellite Remote Sensing Data." *Science of the Total Environment* 882:163395. https://doi.org/10.1016/j.scitotenv.2023.163395.

Zhou, Z., Z. Li, S. Waldron, and A. Tanaka. 2019. "InSAR Time Series Analysis of L-Band Data for Understanding Tropical Peatland Degradation and Restoration." *Remote Sensing* 11 (21): 2592. https://doi.org/10.3390/rs11212592.