



Review

Challenges and Limitations of Remote Sensing Applications in Northern Peatlands: Present and Future Prospects

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Abstract: This systematic literature review (SLR) provides a comprehensive overview of remote sensing (RS) applications in northern peatlands from 2017 to 2022, utilising various platforms, including in situ, UAV, airborne, and satellite technologies. It addresses the challenges and limitations presented by the sophisticated nature of northern peatland ecosystems. This SLR reveals an increased focus on mapping, monitoring, and hydrology but identifies noticeable gaps in peatland degradation research. Despite the benefits of remote sensing, such as extensive spatial coverage and consistent monitoring, challenges persist, including high costs, underexplored areas, and limitations in hyperspectral data application. Fusing remote sensing data with on-site research offers new insights for regional peatland studies. However, challenges arise from issues like the cost of high-resolution data, coverage limitations, and inadequate field validation data in remote areas. This review suggests refining methodologies, validating with high-resolution data, and addressing these limitations for future research.

Keywords: remote sensing data; northern peatlands; multi-proxy studies; UAV; airborne; satellite; environmental data; hyperspectral data; LiDAR



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1. Introduction

Peatlands are unique and diverse ecosystems that cover only around 3% of the global land surface [1–3]. The distinction between peatlands lies in the type of hydrology, nutrients, plants, and geography of the area. Peatlands are wetlands with an accumulation of decaying organic material that creates layers of peat and are divided into bogs and fens. Bogs are low in nutrients and only receive water from the atmosphere, while fens have a higher nutrient content and are nourished by water from both the atmosphere and the ground. Bogs are generally populated by Sphagnum mosses, sedges, and ericaceous shrubs, whereas fens are characterised by brown mosses, sedges, grasses, and shrubs [4,5]. In the global carbon cycle, peatlands serve as a sink for atmospheric carbon dioxide (CO₂) and store approximately 550 billion metric tons of carbon [1,6]. They also provide various ecosystem services, including water purification, flood control, and habitats for various plant and animal species [7].

Peatlands have recently become increasingly important for climate change mitigation and adaptation [8,9]. This is because peatlands are the most significant terrestrial carbon sinks, and their destruction and degradation can result in the release of large amounts of CO₂ into the atmosphere [10]. Therefore, peatland restoration and management have become critical priorities for many governments and conservation organisations worldwide [11,12].

Despite their importance, various human activities threaten peatlands, including drainage, agriculture, forestry, and mining [2,13]. For example, the drainage of peatlands for agriculture or forestry can lead to the oxidation of peat soil, which releases the stored carbon

into the atmosphere as CO₂ [1,14,15]. Peat extraction for use as fuel or horticultural material can also lead to the degradation of peatlands [16,17]. In addition, peatlands are highly susceptible to climate change because warmer temperatures and shifting precipitation patterns can alter peatland hydrology and vegetation [3,18,19].

Therefore, the conservation and management of peatlands are critical issues for global efforts to mitigate climate change and protect biodiversity [11,20]. It should be noted that restoration efforts are being undertaken to mitigate these issues; however, using traditional field-based methods to monitor the success of these restoration strategies can be difficult and expensive. For instance, remote sensing techniques have emerged as a promising alternative for assessing peatland conditions, estimating gaseous carbon fluxes at various scales, and uncovering hidden complexities.

Remote sensing is a powerful tool for mapping and monitoring the characteristics and dynamics of peatlands. It involves acquiring data on the Earth's surface from a distance using sensors on satellites, aircraft, unmanned aerial vehicles (UAVs), and ground-based platforms [21]. Various types of remote sensing data, including visible and infrared imagery, radar [15,22], and LiDAR [23–26], can be used to extract information about the physical, chemical, and biological properties of peatlands [27].

Remote sensing has been widely applied in peatland research and management in recent years, and there is a growing body of literature on this topic. For example, remote sensing technology has been employed to map peatland vegetation cover [28–31], assess peatland hydrology [12,32,33], and estimate carbon storage [10,34]. However, much of the existing research has focused on specific remote sensing platforms, and there have been few attempts to synthesise and compare findings across studies.

Satellite-based remote sensing is one of the most widely used platforms in peatland research and management, as it has revolutionised our understanding of peatland ecosystems by providing large-scale coverage and long-term monitoring capabilities. Satellites orbit the earth from a distance of several hundred kilometres and are equipped with sensors that detect different wavelengths of electromagnetic radiation, such as visible light, infrared, and radar [34–36]. They offer several advantages for peatland applications, including global coverage, repeatability, and relatively high spatial and temporal resolution [37]. Studies such as Metzger et al. (2017) have delved into the impact of land-use intensity on vegetation indices, photosynthesis, and biomass within intensively and extensively managed grassland fens [38]. The analysis of satellite imagery has allowed for the assessment of vegetation dynamics and ecosystem exchange, as Kalacska et al. (2018) demonstrated in their comparison between satellite and airborne imagery for estimating peatland water table depth and net ecosystem exchange [18]. However, satellites also have limitations, such as the need for cloud-free conditions and limited ability to penetrate vegetation canopies [39,40].

Meanwhile, airborne remote sensing platforms, such as aircraft-mounted sensors, offer several advantages for peatland applications, including high spatial and spectral resolution, the ability to acquire data under a wide range of atmospheric conditions, and the ability to cover large areas quickly [25,41,42]. These advancements in technology have facilitated the mapping of peatland attributes, as exemplified by Arroyo-Mora et al. (2018) in their implementation of an airborne-hyperspectral system for the evaluation of maximum gross photosynthesis and uptake efficiency of CO₂ in ombrotrophic peatland [43]. However, airborne remote sensing can be costly, time-consuming, and requires specialised aircraft and trained personnel [44,45].

UAV-based remote sensing involves sensors on small, unmanned aircraft (drones). It has emerged as a versatile tool for peatland research, enabling ultra-high-resolution mapping and monitoring [46]. UAVs offer several benefits for peatland applications, including low cost, ultra-high spatial and temporal resolution, and access to difficult-to-reach areas. Rahman et al. (2017) introduced a new method to map groundwater tables in peatlands using UAVs, highlighting the potential of this platform in hydrological investigations [47]. A study by Lovitt et al. (2018) showcased the utilisation of UAVs

to uncover the effects of low-impact seismic lines on surface morphology, hydrology, and methane release within a boreal treed bog [32]. UAVs have also been employed in mapping peatland vegetation and quantifying carbon stocks, as Diaz-Varela and his team demonstrated in their 2018 examination of bog–heathland mosaics employing exceptionally detailed imagery [48]. However, UAVs also have limitations, requiring skilled operators and having limited payload capacity [23].

In situ-based remote sensing complements remote sensing data by providing ground truth measurements and detailed characterisation of peatlands. Lees et al. (2020) utilised spectral indices for the estimation of gross primary productivity (GPP) and water content, mainly in Sphagnum moss and other plant species in peatland, bridging the gap between field measurements and remote sensing [49]. McPartland et al. (2019) used in situ observations to examine how boreal peatland community composition and Normalized Difference Vegetation Index (NDVI) responded to alterations in hydrology, warming, and elevated carbon dioxide levels. However, in situ- and ground-based remote sensing can be labour-intensive, time-consuming, and is typically limited to small areas [50].

Furthermore, integrating multiple remote sensing platforms, such as satellites and UAVs, has shown promise in enhancing peatland monitoring, such as combining high spatial resolution with global coverage or accessing difficult-to-reach areas with high temporal resolution [51]. Räsänen et al. (2020, 2019) delved into exploring ultra-high spatial resolution remote sensing techniques and their practical applications in mapping vegetation patterns while assessing the necessary data and resolution criteria [30,51]. These approaches allow for a comprehensive understanding of peatland dynamics, emphasised in their research, which involved modelling and scaling up ecosystem respiration and using thermal cameras and UAVs.

Remote sensing techniques and platforms have many applications in peatland research. However, the choice of platform depends on the specific objectives and constraints of the study, as each platform has advantages and limitations. Therefore, in the following sections of this systematic literature review (SLR), we examine the use of different remote sensing platforms for peatland applications in more detail.

The systematic literature review is organised into several sections. The Introduction (Section 1) overviews the study’s objectives and summarises previous reviews. Section 2 details the methodology of the review, including the criteria for study inclusion and exclusion. The included studies are highlighted in Section 3, with a categorisation ranging from satellite-based to ground-based measurements and multiple platforms. Section 4 explores utilising remote sensing platforms and their applications in peatlands. Section 5 compares remote sensing platforms and their applications in northern peatlands. Finally, Section 6, titled “Conclusion”, encapsulates general conclusions and offers insights for future research.

1.1. Aim and Scope of This Systematic Literature Review

In this systematic literature review, an exploration is undertaken to investigate the applications of remote sensing techniques in peatland research. This examination considers the diverse array of remote sensing platforms, encompassing satellites, airborne platforms, UAVs, in situ- or ground-based measurements, and the integration of multiple platforms. This review includes only peer-reviewed research articles published in English in the past six years and is limited to studies conducted on peatlands located in the northern hemisphere, typically at latitudes higher than 23°N, referred to here as northern peatlands.

The objectives of this systematic literature review are as follows:

1. Present an overview of the current knowledge on using remote sensing for mapping and assessing peatland characteristics such as vegetation cover, hydrology, and carbon storage;
2. Evaluate the capabilities and limitations of different remote sensing platforms for peatland applications, including satellite, airborne, UAV, in situ ground-based, and multiple platforms;

3. Identifying the key challenges and opportunities for remote sensing monitoring and management of peatland dynamics, such as land cover/land use change, hydrological fluctuations, and greenhouse gas emissions;
4. Synthesise this review's findings and provide recommendations for future research and remote sensing applications in peatland research.

1.2. Current Literature Reviews

This SLR identified six review articles (Table 1). Czapiewski and Szumińska (2022) assessed remote sensing techniques in research involving peatlands and the external factors affecting their development. The study was a state-of-the-art review and found that there had been a surge in the utilisation of RS approaches in peatland research over the past ten years, likely due to the augmented access to a variety of RS data sets and the quick progress of open-source software [52].

Dronova et al. (2021) conducted a scoping review to evaluate UAVs' current and potential wetland applications. The authors found that UAVs could reduce the logistical demands of field surveys and optimise UAV-based workflows for monitoring wetland environments and management strategies. In addition, they identified significant trends in applications, technology, and data, and provided recommendations for future research [53].

Mirmazloumi et al. (2021) assessed the use of remote sensing (RS) technology in wetland studies in Canada. The study was a bibliographic analysis, and the authors found that most wetland classification studies were conducted within the province of Ontario, with a preference for pixel-based supervised classifiers as the primary classification algorithm [54].

Minasny et al. (2019) conducted a state-of-the-art review of the current digital mapping techniques used to measure and monitor carbon stocks in peatlands and the potential opportunities and challenges to accurately assessing the world's peatlands. The authors found that interest in utilising satellite imagery and other digital mapping technologies to map peatlands was increasing. However, they noted that assessing the accuracy or uncertainty of the prediction was rarely performed [3].

Lees et al. (2018) conducted a literature review to assess the current understanding of estimating carbon dioxide fluxes in peatland utilising remote sensing technology and identified areas for future research. The authors found that there was potential for remote sensing to be utilised in models of carbon fluxes over northern peatlands. However, further development was necessary to create more comprehensive carbon cycle models and ensure their longevity, notably on peatlands subject to restoration [34].

Guo et al. (2017) conducted a literature review to provide an overview of wetland remote sensing, including selected approaches, findings, and types of remote sensors. The review concluded that early research into wetland mapping utilised aerial photography as the primary data source, though hyperspectral imaging had become more prevalent in recent years. They also noted that radar data are often used to detect wetland areas, and LiDAR data can generate three-dimensional topographical maps [4].

This SLR distinguishes itself by offering a specialised and detailed exploration of the applications, challenges, and future directions of RS in northern peatland research. Unlike previous overviews that broadly discuss RS adoption, our focus extends to specific applications such as the integration and the sensor fusion of hyperspectral and LiDAR data for precise vegetation mapping. We address challenges rigorously, emphasising the importance of calibration, validation practices, and interdisciplinary approaches, setting our review apart from general recommendations provided in prior works. Additionally, our comprehensive exploration covers various applications, including vegetation mapping, hydrology monitoring, and carbon stock assessment, providing a more holistic perspective compared to reviews that primarily focus on carbon flux estimation. This SLR goes beyond emphasising the significance of interdisciplinary approaches, stressing the need for data integration and advanced modelling techniques to enhance our understanding of peatland ecosystems, making it a forward-looking contribution to the field.

Table 1. A summary of previous reviews on the use of remote sensing in wetlands and peatlands.

References	Scope	Protocol	Databases Searched	Number of Articles	Timespan	Key Findings
[52]	This research delivers a comprehensive assessment of the use of remote sensing (RS) techniques in peatland research and the external factors that can influence the way they evolve.	State-of-the-art review ⁽¹⁾	Web of Science and Scopus	59	2010–2021	There has been a conspicuous rise in adopting RS methodologies within peatland research in the past decade. This surge can largely be attributed to enhanced accessibility to a diverse range of RS datasets, including Sentinel 1 and 2, Landsat 8, and SPOT 6 and 7, alongside the rapid progress of open-source software tools such as ESA SNAP, QGIS, and SAGA GIS.
[53]	The aim of this study was to examine the present and prospective capabilities of unmanned aerial vehicles (UAVs) in wetlands to enhance ecosystem management practices. It investigates the status of UAV applications in wetlands and identifies several research, technological, and data prerequisites for optimising their effectiveness.	Scoping review ⁽²⁾	Web of Science, ProQuest, and Google Scholar	122	Before 6 March 2021	This review examines the potential of UAVs to reduce the logistical demands of field surveys and to optimise UAV-based workflows for monitoring wetland environments and management strategies. Additionally, it identifies significant trends in applications, technology, and data, and provides recommendations for future research.
[54]	This research article employs meta-data analysis to assess the contemporary status and evolution of wetland studies in Canada through RS technology.	Bibliographic analysis ⁽³⁾	Web of Science and Elsevier Scopus	300	1976–2020	Many wetland classification studies were conducted within the province of Ontario, with a preference for pixel-based supervised classifiers as the primary classification algorithm.
[3]	This article delivers an overview of the present digital mapping techniques for measuring and monitoring carbon stocks in peatlands and potential opportunities and challenges for accurately assessing the world's peatlands.	Critical review ⁽⁴⁾	Not mentioned	90	Not mentioned	This study shows a growing interest in using satellite imagery and other digital mapping technologies to map peatlands. Previous studies used RS, ecology, and environmental field studies to determine peat extent but rarely assessed the accuracy or calculated the prediction's uncertainty. Enhancing the accuracy of peatland mapping can be achieved by incorporating multiple covariates, including optical and radar products, alongside implementing nonlinear machine learning algorithms.

Table 1. Cont.

References	Scope	Protocol	Databases Searched	Number of Articles	Timespan	Key Findings
[34]	This review paper assesses the current understanding of estimating carbon dioxide fluxes in peatland utilising remote sensing technology and identifies areas for future research.	Narrative Review ⁽⁵⁾	Not mentioned	Not mentioned	Not mentioned	The study demonstrated the potential of RS in modelling carbon fluxes across northern peatlands. Nonetheless, further research is imperative to develop more comprehensive carbon cycle models, with particular emphasis on peatlands undergoing restoration, to ensure the sustainability and durability of these models.
[4]	This paper provides an in-depth examination of wetland remote sensing, which involves an overview of selected approaches, findings, and remote sensor types. It also offers recommendations for future wetland research.	Narrative Review ⁽⁵⁾	Science Citation Index Extended (SCIE)	250	till 11 May 2016	Aerial photography was used as the primary data source in early wetland mapping research. This data was typically of medium resolution, though some studies did use higher-resolution imagery. Hyperspectral imaging has grown in popularity in recent years. Furthermore, radar data are frequently used to detect wetland areas, and LiDAR data can be used to generate three-dimensional topographical maps.

⁽¹⁾ State-of-the-art review: a specialised literature review that provides an up-to-date overview of the latest advancements and research findings in a specific field or topic. ⁽²⁾ Scoping review: Used to map the existing literature on a broad topic, identify gaps in knowledge, and clarify key concepts. It does not typically assess individual studies' quality but provides a broad overview of the field. ⁽³⁾ Bibliographic analysis: this research method systematically examines and evaluates bibliographic data to understand trends, relationships, and patterns within a body of literature on a specific topic. ⁽⁴⁾ Critical review: This type of review emphasises a critical assessment of the quality, relevance, and limitations of existing literature. It aims to identify strengths and weaknesses in the research and may involve a detailed critique of methodology and findings. ⁽⁵⁾ Narrative review: A comprehensive literature overview on a particular topic. It summarises key findings, concepts, and theories without a specific methodological approach and is often used to establish the background and context for a research study.

2. Materials and Methods

The majority of systematic reviews follow an extensively used methodology known as “Preferred Reporting Items for Systematic Reviews and Meta-Analyses” (PRISMA) [55]. Nevertheless, our systematic literature review was performed by adapting and combining a technique based on the PRISMA statement and published procedures [56]. The methodologies utilised in the current review enabled the authors to obtain a holistic vision, strengthening the research’s validity through accurate evaluations of the present research by wisely finding and categorising the relevant literature.

Pickering and Byrne (2014) used this technique for finding, selecting, and categorising articles, extracting data, and synthesising their results; it involves 15 steps explicitly described in advance, minimising any biases that might emerge in some narrative and traditional reviews [56].

Additionally, the PRISMA statement augmented our work by guiding the implementation of a four-phase flow diagram (Figure 1) covering record identification and screening, study eligibility, and finally, studies included.

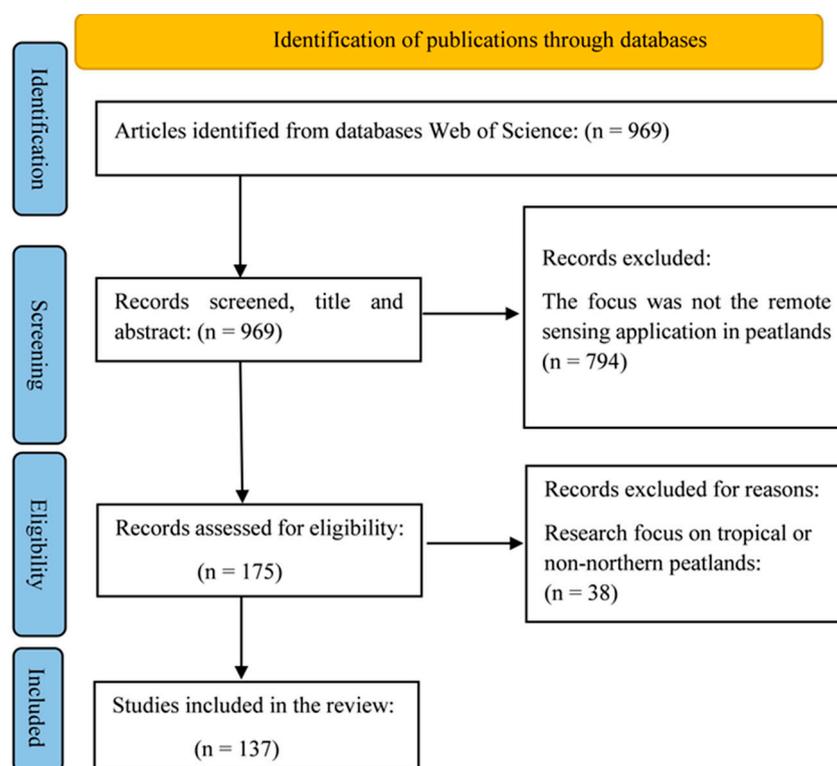


Figure 1. PRISMA chart summarising the database search, screening, and inclusion workflow.

2.1. Identification of Relevant Literature

A systematic approach was taken in all review processes, beginning with selecting the period for the search criteria on the electronic database. As a result, the Web of Science database was chosen for its comprehensiveness, breadth, and high quality. Furthermore, the Science Citation Index Expanded (SCI-Expanded) database within the Web of Science platform is frequently utilised for bibliometric research across various multidisciplinary scientific domains. It includes over 21,000 journals in 254 Web of Science subject areas [57].

The methodology employed for this search involved setting the default beginning for the database time range from 1988 to 2022 to determine the year in which publications on remote sensing in peatland research increased more rapidly. Figure 2 illustrates a significant escalation in the quantity of records during the 2017–2022 period. The annual publication rate within this interval surged from approximately 5 to nearly 18 articles, as evidenced in Figure 2. This trend underscores the relevance of this time frame in encapsulating the most

recent advancements in the field. Consequently, articles published from January 2017 to December 2022 were considered in our study to implement the selection criteria.

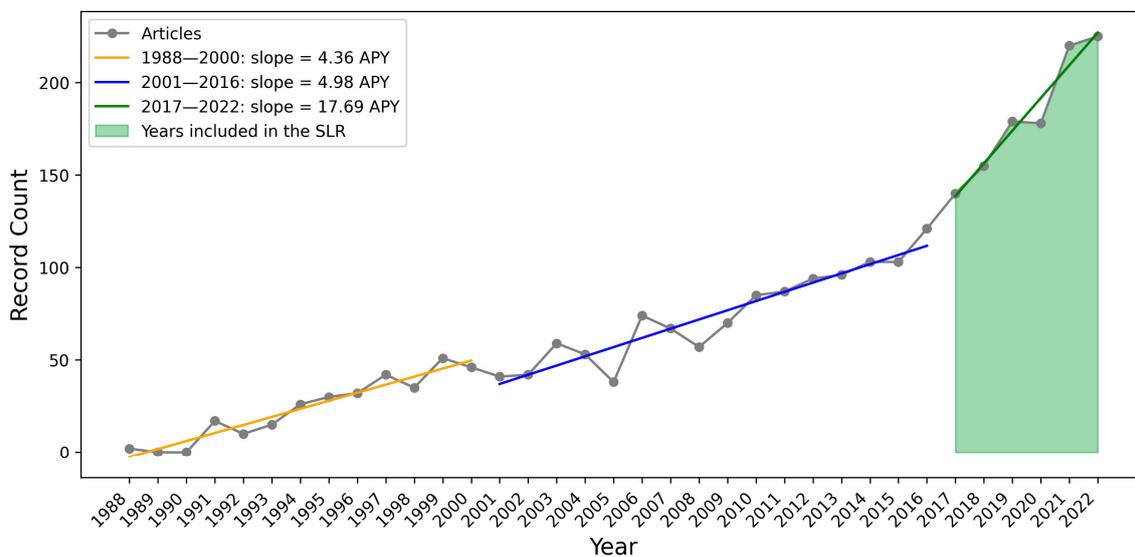


Figure 2. The publications on peatland and remote sensing from 1988 to 2022. APY—articles per year.

2.2. The Database and Search Criteria

The literature search was initially carried out on the Web of Science database as of 30 December 2022, employing the search strategy outlined in Table 2.

Table 2. Literature search keywords and strategy.

Component	Attributes
Search keyword sets	Set 1 (peatland): (TS ^a = (peatland OR mire OR fen OR bog)) Set 2 (remote sensing): TS ^a = (“remote sensing” OR UAV OR NDVI OR “Normalised Difference Vegetation Index” OR “Unmanned Aerial Vehicle” OR SIF OR “Solar-Induced Chlorophyll Fluorescence” OR airborne OR LiDAR OR satellite OR “Sun-Induced Chlorophyll Fluorescence” OR “reflectance” OR EVI OR “Enhanced Vegetation Index” OR PRI OR “Photochemical Reflectance Index” OR indices OR indexes OR spectra* OR multispectral OR hyperspectral OR “VI” OR “vegetation indices”))
Search strategy	Utilise keywords from both Set 1 and Set 2. Conduct searches using titles, abstracts, and keywords. Focus on publications in the English language. Select “Article” document types exclusively, excluding review papers, conference proceedings, grey literature, or book chapters. Limit the timeframe of consideration to the period from 1 January 2017 to 30 December 2022.

^a TS = topic. The asterisk (*) was used to broaden the search and retrieve variations of the term with different suffixes, e.g., spectra* consider spectral and spectra.

The methodology involved exporting all results from the database as BibTex to Mendeley Desktop and as an Excel spreadsheet for subsequent processing.

2.3. Screening the Literature

The articles had to adhere to the following criteria to be included: (1) they had to be original, English-language research papers published in peer-reviewed scientific journals, and (2) they had to include any application of any remote sensing platforms on peatlands. Books, abstracts, theses/dissertations, “grey literature”, and any documents dealing with tropical peatlands were excluded to ensure that only original research and peer-reviewed articles focused on remote sensing applications in northern peatlands were included. Review articles were included only if they presented original research but were

not included in the subsequent data analysis. It is worth noting that the authors searched the bibliography for eligible articles to verify that all relevant articles were identified. This likely ensured that the final list of studies was relevant and that the review was extensive, consistent, and effective. The PRISMA flow chart (Figure 1) shows the workflow of identifying, screening, and including final articles. The concluding dataset contained 137 full-text articles published between 2017 and 2022.

2.4. Extracting Data and Synthesising Results

The remaining peer-reviewed studies (137) were found to be highly pertinent to remote sensing in peatlands. After filtering and evaluating them, possible effective scaling options were revealed. Subsequently, we identified five primary clusters—papers that relied on (1) satellite-, (2) airborne-, (3) UAV-, or (4) in situ/ground-based remote sensing measurements in peatlands, and papers that used (5) multiple remote sensing platforms in peatland studies.

The classification of the five primary clusters was further refined by their corresponding subclusters, which follow the electromagnetic spectrum in ascending order of frequency. The subclusters commence with passive remote sensing—specifically, optical remote sensing—and continue with active remote sensing techniques, including Light Detection and Ranging (LiDAR). Finally, the subclusters culminate with Radio Detection and Ranging (Radar) remote sensing. It should be emphasised that this classification scheme is predicated on frequency, with lower-frequency domains being represented earlier in the sequence. For the synthesising of results, the following elements of information were extracted from each original research publication that met the inclusion criteria: (1) the author(s), (2) the year of publication, (3) the journal, (4) the country of study site, (5) the peatland type, (6) the dominant vegetation, (7) remote sensing platforms, (8) sensors used, (9) study focus and concern, (10) the study result, and (11) future work and limitations.

3. Current Remote Sensing Data

Remote sensing data employed in peatlands can be broadly categorised into passive and active sensors. Passive sensors detect radiation naturally emitted or reflected by a target, while active sensors emit energy and then measure how much of it is reflected or scattered back by the target. Passive sensors are sensitive to the electromagnetic spectrum's visible, near-infrared, and thermal infrared regions and help collect information regarding the target's reflectance properties and surface temperature. Active sensors like LiDAR and radar capture terrain information and subsurface characteristics. The choice of sensor type depends on the specific application and required information. For example, passive sensors are typically used for collecting spectral information, e.g., multispectral and hyperspectral imagery, which provide valuable insights into vegetation dynamics and environmental variables, while active sensors are used to determine structural and height information. Combining both sensor types can provide a more comprehensive view of the target.

Figure 3 presents a comprehensive overview, encapsulating research studies focusing on remote sensing applications in peatlands. This SLR is thoughtfully organised based on the chosen platform for remote sensing, including satellite, airborne, unmanned aerial vehicle (UAV), in situ, and mixed (a fusion of platforms). Furthermore, the studies are systematically categorised by the sensing they employ, which can be active (active remote sensing), passive (passive remote sensing), or "Act+Pas" (a combination of active and passive sensing methods).

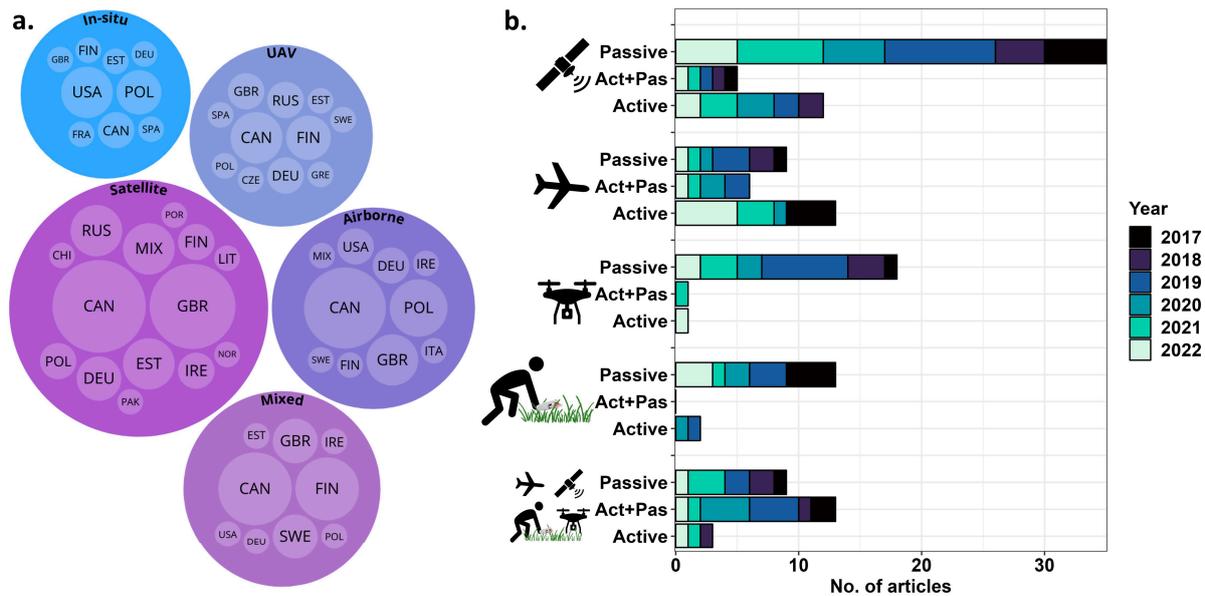


Figure 3. Number of articles distributed by type of platform and country of study; (a) the code of the country of study based on ISO 3166-1 alpha-3 codes (MIX stands for several countries in one study), where the size is controlled by the number of articles in each category, the distribution of articles per remote sensing data source (satellite, airborne, UAV, in situ and mixed plus active, passive, or Act+Pas, which stands for mixed or sensor fusion), and the year of study (b).

These included studies cover a spectrum of years from 2017 to 2022, with Figure 3b revealing the number of articles or studies related to each category. These valuable insights shed light on the distribution of research efforts within the remote sensing applications in peatlands. This resource equips researchers and practitioners with a profound understanding of evolving trends and focal points across different platforms and sensing types over the years.

The trends highlighted in Figure 3 indicate technology's adaptability in addressing the unique challenges posed by peatland environments. These include the transition from active to passive sensing and its dominance in satellite applications, the increasing prevalence of active airborne sensing, and the growing adoption of the fusion of sensors in "Act+Pas" multiplatform applications. Moreover, they underscore the global relevance of peatland research, with many countries such as Canada, Finland, Great Britain, and Poland contributing to this dynamic field (Figure 3a). This insight is a critical resource for anyone interested in the advancements and shifts in remote sensing methodologies applied to peatlands, allowing for more informed research and decision-making in this vital environmental domain.

4. Remote Sensing Platforms Used in Peatland Research

4.1. Satellite-Based Remote Sensing

The literature reveals that satellite-based remote sensing techniques have been widely used for peatland research. It has emerged as a valuable tool for monitoring and studying peatland ecosystems [58]. In recent years, the application of satellite data has emerged as a promising approach to assessing the condition of peatlands [11,59–61], estimating carbon fluxes [37,62,63], and monitoring the effectiveness of restoration initiatives [64]. In this section, we evaluate the effectiveness and limitations of satellite-based remote sensing applications in peatland research (Table 3), focusing on their contribution to peatland mapping, vegetation monitoring, and carbon stock estimation.

4.1.1. Peatland Mapping

Satellite-based remote sensing has significantly advanced peatland mapping [11]. Several studies have developed methodologies to classify wetlands from multiple satellite remote-sensing data sources using advanced classification algorithms [39,65,66]. These methodologies effectively discriminate between different wetland classes, such as bog, fen, marsh, swamp, and shallow water [39,66], demonstrating the capability of high-resolution satellite imagery to identify and delineate different peatland types.

Multispectral sensors have allowed for detecting subtle variations in vegetation and soil properties [40,67]. However, despite these advancements, challenges exist, particularly in areas with dense vegetation cover or mixed land use, such as peatlands [68]. Additionally, the accuracy of peatland classification algorithms can be affected by the presence of shadows, cloud cover, and atmospheric interference in the case of utilising passive-based remotely sensed data [65]; thus, utilising Synthetic Aperture Radar (SAR) data is helpful for overcoming the challenges of cloud cover and shadows. Various SAR sensors are operational, offering multiple options between and within a single sensor. When selecting a SAR sensor for peatland mapping, considerations such as wavelength (e.g., L-band, X-band, and C-band), polarization options (with fully polarimetric sensors providing more information than dual- or single- polarisation sensors), and spatial resolution are crucial. L-band has demonstrated the ability to provide distinctive information about peatland surfaces and is relatively insensitive to vegetation variability [69]. Nonetheless, given the intricate nature of peatland ecosystems, acquiring sub-metre resolution data is imperative for accurately mapping the sporadic patterns of peatland vegetation. It is important to note that such high-resolution data acquisition is associated with associated costs [28].

4.1.2. Vegetation Dynamics and Productivity Monitoring

Several studies have explored using satellite data to analyse peatland vegetation dynamics and productivity [66,70]. The utilisation of NDVI derived from satellite data has become a prevalent method for evaluating the health and productivity of vegetation [64,71]. Moreover, integrating high-resolution optical and radar imagery enables the detection and monitoring of vegetation changes associated with peatland degradation and restoration efforts [11,60].

Pang et al. (2021) examined remotely sensed vegetation phenological parameters in Chinese bogs using MOD13Q1-EVI data, highlighting the potential of satellite imagery in monitoring long-term phenological changes [70].

Räsänen et al. (2019) explored mapping above-ground biomass using very high spatial resolution (VHSR) satellite imagery from platforms like QuickBird, WorldView-2, and WorldView-3. They underscored the significance of integrating precise in situ data to enhance the precision of biomass estimation [71].

However, limitations arise when analysing dense and tall vegetation in peatland areas, as the penetration of radar signals is reduced. Consequently, satellite-based SAR/LiDAR remote sensing may underestimate vegetation biomass and structure. Moreover, as NDVI is mainly used not only in peatland research but in remote sensing in general, such an index is relatively stable; for instance, in peatland vegetation, NDVI is well-correlated with the vascular plants' phenology, but the correlation with *Sphagnum* spp. is not well determined.

4.1.3. Carbon Stock Estimation

Quantifying carbon stocks in peatlands is crucial for understanding their role in the global carbon cycle. Satellites provide a means for estimating carbon stocks over large areas. Several studies have utilised satellite data to map and estimate peatland carbon content [62,63,72,73]. However, obtaining accurate carbon estimation through satellites requires ground validation and considering site-specific factors, such as vegetation type, peat depth, peat thickness, or direct traditional carbon content estimation in the laboratory. By combining spectral indices with field measurements, these studies have demonstrated the potential of remote sensing in capturing spatial variations in peatland carbon stocks.

4.1.4. Monitoring Restoration Efforts and Success

Monitoring the success of peatland restoration initiatives is crucial for assessing the effectiveness of these schemes. Hence, accurate above-ground biomass estimation is essential for understanding peatland carbon storage. Medvedeva et al. (2017) assessed the capabilities of multispectral satellite data, such as Landsat-7 ETM+, Spot-6 HRG, and Spot-5 HRG, in identifying the condition of peatlands impacted by peat extraction and abandoned deposits [74]. They demonstrated the potential of remote sensing for monitoring biomass changes and evaluating the effectiveness of restoration measures. Pang et al. (2021) investigated remotely sensed vegetation phenological parameters in bogs, emphasising the potential of satellite data in monitoring long-term vegetation phenology and its implications for ecological processes and carbon dynamics [70]. In their respective investigations, Lees et al. (2019) and Artz et al. (2019) employed Moderate Resolution Imaging Spectroradiometer (MODIS) datasets to develop models for estimating gross primary productivity (GPP) in peatland ecosystems undergoing restoration [59], comparing the results with field measurements and introducing a Temperature and Greenness model for more accurate local-scale assessments [64].

Peatlands store large amounts of carbon, the release of which depends strongly on water table depth (WTD) [75]. Hence, the peatland's water table must be monitored to ensure restoration success [75,76].

Synthetic Aperture Radar stands out due to its unique ability to penetrate beneath the Earth's surface, reaching the uppermost soil layers. This unique characteristic offers invaluable insights that optical data alone cannot provide. In our pursuit to assess the feasibility of employing remote sensing-derived information for monitoring below-ground ecosystem resilience, we embark on an exploration. A noteworthy aspect is SAR backscatter's capability to estimate soil surface moisture, which has been shown to establish a correlation with the time series of WTD in peatlands and wetlands in general [76,77].

The potential of the Sentinel-1 SAR sensor for tracking the dynamic shifts in soil moisture is substantial. This potential is attributed to its frequent return interval and high spatial resolution, capable of reaching as low as 10 metres. These attributes are precious in high-latitude regions where numerous peatlands are situated. Nonetheless, the capabilities of the Sentinel-1 SAR have not been fully explored due to the recent launch of the satellite pair in April 2014 and April 2016, resulting in a constrained time series of accessible satellite images [78].

It is crucial to highlight that SAR cannot currently be directly utilised for comparing soil moisture across different sites. This limitation stems from the inconsistent relationship between SAR backscatter and soil moisture, which is influenced by factors including vegetation structure and surface topography [76,77].

4.1.5. Monitoring Peatland Fire Dynamics

Peatland fires have severe environmental and socio-economic impacts. Satellite-based fire monitoring systems have been developed to understand fire dynamics and mitigate their effects. Millard et al. (2022) investigated seasonally decomposed Sentinel-1 backscatter time series in Canada's boreal forest as indicators of wildfire vulnerability in peatland [79]. They emphasise the potential of SAR backscatter data as a nearly real-time tool for predicting fire vulnerability over extensive geographic areas. However, they also acknowledge certain limitations [79]. The method's effectiveness relies on the continuous acquisition of SAR data, making it susceptible to disruptions resulting in an incomplete time series dataset. Moreover, implementing this method necessitates substantial computing resources for generating spatial estimates. Nevertheless, the study highlights the potential of using seasonally decomposed Sentinel-1 backscatter time series to indicate peatland wildfire vulnerability, contributing to peatland fire occurrence [79].

4.1.6. Challenges and Limitations

Satellite-based remote sensing has revolutionised peatland research by providing a comprehensive view of these complex ecosystems. It has proven effective in peatland mapping, vegetation monitoring, and carbon stock estimation due to large-scale coverage, cost-effectiveness, and the ability to capture seasonal dynamics and spatial variations. However, several limitations and challenges need to be addressed. These include improved calibration and validation of satellite products, considering local-scale factors and site-specific characteristics, and incorporating detailed in situ data for accurate assessments. Furthermore, utilising satellite data for peatland monitoring requires careful selection of appropriate vegetation indices, spectral bands, and processing techniques to capture these ecosystems' complex dynamics and heterogeneity.

Moreover, challenges related to classification accuracy, vegetation penetration, and quantifying below-ground carbon stocks persist. Continued technological advancements, multi-sensor data integration, and improved algorithms are necessary to overcome these limitations. Furthermore, ground validation and site-specific considerations remain crucial to ensure accurate and reliable results in satellite-based remote sensing applications on peatlands.

Although the emergence of hyperspectral satellite data made possible by upcoming missions such as EnMAP, PRISMA, and CHIME presents an exciting leading edge in peatland vegetation monitoring, there is a lack of hyperspectral satellite data studies, which is crucial to be included in future research as these new datasets, characterised by their extensive spectral coverage, hold the potential to delve into species-level analysis. The complexity lies in harnessing the full spectral extent of these novel hyperspectral satellite data sets, which calls for accurate measurements of the spectral properties specific to key plant species. Understanding and exploring these spectral characteristics are indispensable to unlocking the immense possibilities.

Table 3. Commonly used satellites and their applications found in the literature.

References	Peatland Type *	Peatland Status	Dominant Vegetation	Platform	Sensor/Product	Indices	Sensing Type	Multi/Hyper	Application
[14]	Peatland	Disturbed	No vegetation (bare peat)	Landsat	TM, OLI	NDVI	Passive	Multi	Change Detection
[60]	Bog	Disturbed	<i>Sphagnum</i> spp., other mosses, lichen, <i>Ericaceous</i> shrubs, sedges, grasses	Sentinel-1	C-band SAR	NA	Active	NA	Condition assessment
[11]	Bog	Restored	NA	ERS1, ERS2, Sentinel-1	C-band SAR	NA	Active	NA	
[9]	Peatland	Natural	<i>Sphagnum</i> spp., <i>Juniperus brevifolia</i>	Sentinel-2, Rapideye	NA	NA	Passive	NA	Hydrologic services estimation
[80]	Bog	Natural	<i>Sphagnum</i> spp., <i>Pinus sylvestris</i> , <i>Calluna vulgaris</i> , <i>Eriophorum vaginatum</i> , <i>Chamaedaphne calyculata</i> , <i>Andromeda polifolia</i> , <i>Rhynchospora alba</i> , <i>Ledum palustre</i> , <i>Oxycoccus microcarpus</i> , <i>Oxycoccus palustris</i>	Landsat, Terra	TM/MOD11A1	NDVI, SMI, Albedo	Passive	Multi	Monitoring WTD dynamics
[81]	Peatland	Natural	Mosses, sedges, shrubs, sparse dwarf pines, shrubs, black spruce, mosses, downy willows, and dwarf birch, Alder, willow	Landsat, Terra	MOD09GA	NA	Passive	Multi	
[76]	Peatland	Restored	NA	ENVISAT	ASAR C-Band	NA	Active	NA	
[78]	Fen	Disturbed	Grass	Sentinel-1	C-band SAR	NA	Active	NA	
[82]	Peatland	Restored	NA	Sentinel-1, Sentinel-2	C-Band GRD/MSI	NDWI, MNDWI	Mixed	Multi	
[39]	Peatland	NA	NA	RADARSAT-2, Sentinel-1, ALOS-2	C-band, L-band SAR	NA	Active	NA	
[65]	Peatland	NA	NA	Landsat, RADARSAT-2, Sentinel-1	MSI/C-band, L-band SAR	NDVI, NDWI, Albedo, LST	Mixed	Multi	Peatland classification
[68]	Peatland	NA	NA	RapidEye	NA	RENDVI, RVI, GNDVI	Passive	Multi	
[66]	Peatland	NA	NA	Sentinel-1, Sentinel-2	Ground Range Detected (GRD)	NDVI, EVI, DVI, RENDVI, NDWI	Mixed	Multi	
[83]	Peatland	Disturbed	NA	Radarsat-2, Landsat	SAR/OLI	NA	Mixed	Multi	

Table 3. Cont.

References	Peatland Type *	Peatland Status	Dominant Vegetation	Platform	Sensor/Product	Indices	Sensing Type	Multi/Hyper	Application
[37]	Mire	Disturbed	<i>Molinia caerulea</i> , <i>Potentilla erecta</i>	Terra	MOD9A1, MOD13Q1, MOD15A2, MOD17A2	NDVI, EVI, LAI, fPAR,	Passive	Multi	
[72]	Peatland	Natural	<i>Sphagnum fuscum</i> , <i>Chamaedaphne calyculata</i> , <i>Picea mariana</i> , <i>Eriophorum vaginatum</i> , <i>Dicranum fuscescens</i> Turner, <i>Tomentypnum nitens</i> , <i>Larix laricina</i> , <i>Betula pumila</i> , <i>Menyanthes trifoliata</i> , <i>Carex lasiocarpa</i>	Landsat	OLI	EVI	Passive	Multi	
[63]	Peatland	Natural	<i>Carex rostrata</i> , <i>Betula nana</i> , <i>Eriophorum angustifolium</i> , <i>Sphagnum fuscum</i> , <i>S. angustifolium</i> , <i>S. riparium</i> , <i>S. fallax</i> , <i>S. balticum</i> , <i>S. Lindbergii</i> , <i>S. majus</i> , <i>Empetrum hermaphroditum</i> , <i>Menyanthes trifoliata</i> , <i>Eriophorum vaginatum</i> , <i>Vaccinium oxycoccos</i> , <i>Andromeda polifolia</i> , <i>Trichophorum caespitosum</i> , <i>Carex chordorrhiza</i> , <i>Salix phylicifolia</i> . <i>Betula nana</i> , <i>Salix lapponum</i> ,	Terra, Sentinel-2	MOD11A1, MYD11A1/MSI	EVI, NDWI	Passive	Multi	Peatland CO ₂ gas fluxes
[62]	Bog	Disturbed	<i>Molinia caerulea</i> , <i>Potentilla erecta</i>	Terra	MODIS9A1	NDVI	Passive	Multi	
[84]	Bog	Disturbed	<i>Scirpus cespitosus</i> , <i>Eriophorum vaginatum</i> , <i>Molinia caerulea</i> , <i>Narthecium ossifragum</i> , <i>Sphagnum</i> spp.	Terra	MOD15A2, MODIS9A1	NDVI, fPAR	Passive	Multi	
[85]	Peatland	Disturbed	<i>Picea mariana</i> , <i>Salix</i> spp., <i>Alnus alnobetula</i>	Landsat	TM&ETM+&OLI	NDVI	Passive	Multi	
[86]	Bog	Natural	<i>Sphagnum</i> spp., <i>Pinus sylvestris</i>	Sentinel-1	C-band SAR	NA	Active	NA	Peatland degradation
[87]	Bog	Disturbed	NA	Geoeye-1	NA	NA	Passive	Multi	
[12]	Bog	Natural	<i>Sphagnum</i> spp., <i>Pinus sylvestris</i>	Terra	MOD09Q1	NDVI	Passive	Multi	Peatland degradation and hydroclimatic conditions

Table 3. Cont.

References	Peatland Type *	Peatland Status	Dominant Vegetation	Platform	Sensor/Product	Indices	Sensing Type	Multi/Hyper	Application
[88]	Peatland	Natural	<i>Sphagnum</i> spp., <i>Carex</i> spp., <i>Pleurozium schreberi</i> , <i>Hylocomium splendens</i> ,	ALOS PALSAR, ERS-1 or 2, Landsat 5 TM	SAR L-band, C-band, ETM+	NA	Mixed	Multi	Peatland mapping
[31]	Peatland	Natural	<i>Sphagnum</i> spp., <i>Carex</i> spp.,	Sentinel-2	MSI	NDVI, EVI, NDWI	Passive	Multi	
[69]	Bog	Disturbed	NA	Sentinel-1, RADARSAT-2	C-band	NA	Active	NA	
[89]	Peatland	NA	NA	Landsat	OLI	NA	Passive	Multi	
[90]	Peatland	NA	NA	Sentinel-1	C-band SAR	Coherence Assessment	Active	NA	
[91]	Peatland	NA	NA	RapidEye	NA	RENDVI, NDVI, GNDVI, Red Edge,	Passive	Multi	
[61]	Bog	Disturbed	<i>Sphagnum</i> spp., shrub, grass, rushes	Sentinel-1	C-Band SAR	NA	Active	NA	Peatland monitoring
[74]	Bog	Disturbed	Willow herb, small reed, and small birch reed communities	Spot-5, Spot-6, Landsat-7 ETM+	HRG/ETM+	NA	Passive	Multi	
[33]	Bog	Disturbed	<i>Eriophorum vaginatum</i> , <i>Sphagnum</i> spp., <i>Molinia</i> spp. dominated, dwarf shrubs	Sentinal-1	NA	NA	Active	NA	
[92]	Bog	Natural	<i>Pinus sylvestris</i> 'Nana', <i>Ledum</i> <i>palustre</i> , <i>Vaccinium uliginosum</i> , <i>Calluna vulgaris</i> , <i>Empetrum nigrum</i> , <i>Sphagnum</i> spp.	Terra	MODIS LST, MOD11A1	NA	Passive	Multi	
[93]	Bog	Disturbed	NA	Sentinel-1	C-band SAR	NA	Active	NA	
[70]	Bog	Natural	<i>Sphagnum</i> spp.,	Terra	MOD13Q1	EVI	Passive	Multi	

Table 3. Cont.

References	Peatland Type *	Peatland Status	Dominant Vegetation	Platform	Sensor/Product	Indices	Sensing Type	Multi/Hyper	Application
[71]	Peatland	Natural	Mosses, sedges, shrubs	QuickBird, WorldView-2 and WorldView-3	NA	NDVI, NDVI, RGI, EVI, EVI, SAVI, MSAVI	Passive	Multi	Peatland productivity
[67]	Bog	Natural	<i>Sphagnum</i> spp.,	Terra	MOD13Q1	NDVI	Passive	Multi	
[73]	Bog	NA	<i>Calluna vulgaris</i> , <i>Empetrum nigrum</i> , <i>Vaccinium uliginosum</i> , <i>Rubus chamaemorus</i> , <i>Dicranum scoparium</i> , <i>Hylocomium splendens</i> , <i>Pleurozium schreberi</i> , <i>Racomitrium lanuginosum</i> , <i>Sphagnum</i> spp., <i>Cladonia</i> spp., <i>Carex rariflora</i>	Terra	MODIS NDVI	NDVI	Passive	Multi	
[94]	Peatland	Disturbed	Sedge, sedge–moss, reed, grass	Sentinel 2, Sentinel 3, Terra	MSI/OLCI, SLSTR/LST/MOD09GQ, MOD11A1	NDVI, NDII, APAR, LAI	Passive	Multi	
[19]	Peatland	Natural	Moss, grass, vascular plants, shrub	Landsat	NA	NDVI	Passive	Multi	
[95]	Fen	Natural	<i>Sphagnum teres</i> , <i>Drosera rotundifolia</i> , <i>Carex limosa</i> , <i>Oxycoccus palustris</i>	Terra and Aqua	MOD13Q1/MYD13Q1	NDVI	Passive	Multi	Peatland restoration
[96]	Bog	Restored	NA	Terra	MOD11-C2, MODIS LST, MCD43A3	NA	Passive	Multi	
[20]	Bog	Restored	Bare peat, scrub, grass, sedge, <i>Calluna Vulgaris</i> , <i>Pteridinium</i> spp.	Terra	MOD13A2, MCD43A3	NDVI, EVI	Passive	Multi	
[59]	Peatland	NA	NA	Terra	NA	EVI, SAVI, NDWI, LST	Passive	Multi	
[64]	Bog	Restored	<i>Eriophorum angustifolium</i> , <i>Sphagnum capillifolium</i> , <i>Cladonia portentosa</i> , <i>Calluna vulgaris</i> , <i>Erica tetralix</i> , <i>Trichophorum germanicum</i> , <i>Molinia caerulea</i> , <i>Polytrichum commune</i> , <i>Dicranum scoparium</i> , <i>Pleurozium schreberi</i>	Terra	MOD17A2H, MOD09A1	NDWI, NDVI, EVI	Passive	Multi	Restoration monitoring
[97]	Bog	Disturbed	<i>Sphagnum</i> spp., <i>Pinus contorta</i> , <i>Betula papyrifera</i> , <i>Betula pendula</i>	Terra	MOD13Q1, MOD16A2 ET	NDVI	Passive	Multi	

Table 3. Cont.

References	Peatland Type *	Peatland Status	Dominant Vegetation	Platform	Sensor/Product	Indices	Sensing Type	Multi/Hyper	Application
[58]	Peatland	Restored	<i>Pine</i> , willow–birch, bare peat	Landsat, Sentinel-2, Spot-5	ETM+, MSI, HRG	RED–NIR, NIR–SWIR, SWIR2–SWIR	Passive	Multi	Fire risk reduction and restoration monitoring
[40]	Mire	Disturbed	<i>Molinia caerulea</i> , <i>Potentilla erecta</i>	Landsat, Sentinel-2, Spot-5, Spot-6	ETM+, OLI, MSI, HRG	RED–NIR, NIR–SWIR2, SWIR2–SWIR	Passive	Multi	
[79]	Peatland	NA	NA	Sentinel-1, Sentinel-2	C-Band SAR/MSI	NDVI, NDII	Mixed	Multi	Wildfire dynamics

* Note: in this table, the term “peatland” is used comprehensively to refer to all peatlands considered in the study unless otherwise specified.

4.2. Airborne-Based Remote Sensing

Among the various remote sensing platforms available, airborne-based remote sensing has gained considerable attention due to its ability to provide high-resolution data over large areas. This section evaluates the strengths and limitations of airborne-based remote sensing applications on peatlands, focusing on the field's key studies. However, at the study level, Table 4 shows the application and sensor used in all the airborne studies.

4.2.1. Peatland Classification and Mapping

Airborne-based remote sensing has proven effective in classifying and mapping peatland vegetation types. Studies by Szporak-Wasilewska et al. (2021) and Carless et al. (2019) demonstrated the ability to distinguish between different peatland vegetation communities using airborne hyperspectral and LiDAR data for the mapping and continuous monitoring of wetland ecosystems [42,44]. Both studies demonstrate the effectiveness of integrating remote sensing products, such as hyperspectral bands, spectral indices, and topographic information, for accurate classification and mapping of wetland habitats. The research by Szporak-Wasilewska et al. (2021) emphasises the potential of combining hyperspectral and LiDAR data to improve classification accuracy [42], while Carless et al. (2019) highlights the advantages of remote sensing over traditional ground surveys for mapping peatland degradation [44]. Furthermore, a study by Langlois et al. (2017) used LiDAR data for boundary delineation in peatland complexes [24].

The studies by Exler and Moore (2022) and Zhang et al. (2018) focus on assessing vegetation traits and water balance in peatland vegetation communities [45,98]. Exler and Moore (2022) quantify throughfall, interception loss, and streamflow across various vegetation communities within a maritime raised bog, highlighting the importance of shrub vegetation in quantifying net precipitation [98]. Zhang et al. (2018) developed a methodology using airborne hyperspectral data to calculate the fractional coverage of various plant functional types within peatland ecosystems, showcasing the effectiveness of the multiple endmember spectral mixture analysis (MESMA) approach [45].

These studies highlight the potential of airborne sensors to provide detailed information on vegetation composition and structure, facilitating peatland management and conservation efforts.

4.2.2. Monitoring Peatland Dynamics, Degradation, and Hydrological Changes

Monitoring peatland hydrological dynamics is crucial for understanding carbon fluxes and ecosystem health. Airborne-based remote sensing techniques like LiDAR have been utilised to estimate water table levels and monitor peatland moisture content. The research by Chasmer and Hopkinson (2017) and Mirosław-Świątek et al. (2017) focus on monitoring peatland dynamics, degradation, and hydrological changes [99,100]. Chasmer and Hopkinson (2017) investigate the connections between the El Niño/Southern Oscillation (ENSO) index and permafrost loss in a watershed, highlighting the accelerated permafrost loss and associated hydrological changes [100]. Mirosław-Świątek et al. (2017) explore the uncertainties in digital elevation models (DEMs) and their impact on water level assessments in riparian and mire ecosystems [99]. They emphasise the need to address the quality of DEMs and the associated uncertainties to ensure accurate and reliable DEM uncertainty in model-based water level assessments for wetland management and ecological assessments.

4.2.3. Peatland Carbon Stock Assessment

Accurate estimation of carbon stocks is essential for assessing peatlands' climate change mitigation potential [41,101,102]. Airborne-based remote sensing, combined with LiDAR technology, has been employed to estimate above-ground biomass and carbon stocks in peatland ecosystems. Studies by O'Leary et al. (2022) presented methods that rely on high-quality airborne radiometric data and prior knowledge of peatland extent, which offer a valuable approach for international peatland mapping projects, enabling the identification of previously unrecognised peat areas and updates to boundary locations [41].

This has significant implications for carbon stock assessment, land management decisions, and rehabilitation projects. It is more suitable for large areas with comprehensive datasets exhibiting clear statistical relationships. The findings can serve as a basis for conducting more targeted, region-specific investigations or integrating them into broader peatland mapping initiatives.

4.2.4. Challenges and Limitations

While airborne-based remote sensing offers significant potential for peatland research, several challenges and limitations must be acknowledged. First, the cost and logistical requirements associated with airborne campaigns can be substantial, limiting the extent and frequency of data acquisition. Weather conditions and cloud cover can impede data collection and affect image quality regarding passive remote sensing data acquisitions. Furthermore, interpreting remote sensing data often requires ground validation, which can be challenging in remote and inaccessible peatland areas. Nevertheless, future research is required, similar to the study by Soffer et al. (2019), which focuses on advancements in the calibration and validation of airborne hyperspectral imagery in Arctic peatland regions [103]. The research demonstrates the importance of rigorous calibration and validation practices in improving the quality and reliability of hyperspectral imagery analysis. Soffer et al. (2019) highlight the implications of their methodology for satellite image analysis, emphasising the need for accurate calibration and validation in peatland ecosystems. This study contributes to the refinement and reliability of airborne remote sensing data analysis in peatland studies [103].

Table 4. Airborne studies, the sensor used, and applications.

Reference	Peatland Type *	Peatland Status	Dominant Vegetation	Active/Passive	Data Type	Application
[42]	Fen	Disturbed	<i>Campylyum stellatum</i> , <i>Hamatocaulis vernicosus</i> , <i>Limprichtia cossonii</i> , <i>Fissidens adianthoides</i> , <i>Scorpidium scorpioides</i> , <i>Carex</i> spp., <i>Comarum palustre</i> , <i>Menyanthes trifoliata</i> , <i>Thelypteris palustris</i> .	Mixed	Hyperspectral & LiDAR	Classification and mapping
[24]	Peatland	Disturbed	<i>Sphagnum</i> spp., <i>Alnus incana</i> , <i>Ilex (Nemopanthus) mucronatus</i> , <i>Rhododendron canadense</i> , <i>Viburnum nudum</i> .	Active	LiDAR	
[25]	Bog	NA	<i>Empetrum nigrum</i> , <i>Calluna vulgaris</i> , <i>Betula nana</i> , <i>Sphagnum</i> spp., <i>Andromeda polifolia</i> , <i>Eriophorum vaginatum</i> .	Mixed	RGB & LiDAR	
[45]	Bog	NA	<i>Calluna vulgaris</i> , <i>Erica tetralix</i> , <i>Myrica gale</i> , <i>Vaccinium myrtillus</i> , <i>Rhyncospera alba</i> , <i>Eriophorum</i> spp., <i>Sphagnum</i> spp., <i>Andromeda polifolia</i> .	Passive	Hyperspectral	
[41]	Peatland	NA	NA	Passive	NA	
[17]	Bog	Disturbed	<i>Pinus mugo</i> , <i>Sphagnum</i> spp.	Mixed	LiDAR & CIR & RGB	
[102]	Peatland	NA	NA	Active	LiDAR	
[44]	Bog	Disturbed	NA	Mixed	Multispectral & LiDAR	
[104]	Bog	Disturbed	NA	Mixed	Gamma-ray & Radar	
[29]	Bog	Natural	NA	Mixed	Gamma-ray & LiDAR	
[43]	Bog	NA	<i>Sphagnum</i> spp., <i>Typha angustifolia</i> , <i>Chamaedaphne calyculata</i> , <i>Rhododendron groenlandicum</i> , <i>Kalmia angustifolia</i> , <i>Vaccinium myrtilloides</i> , <i>Eriophorum vaginatum</i> , <i>Picea mariana</i> , <i>Betula populifolia</i> , <i>Larix laricina</i> .	Passive	Hyperspectral	CO ₂ fluxes
[105]	Peatland	NA	NA	Active	NA	

Table 4. Cont.

Reference	Peatland Type *	Peatland Status	Dominant Vegetation	Active/Passive	Data Type	Application	
[106]	Bog	NA	<i>Sphagnum</i> spp.,	Active	LiDAR	Peatland hydrology and vegetation dynamics	
[107]	Fen	NA	<i>Sphagnum</i> spp., brown moss, feathermoss, herb, graminoid, horsetail, shrub.	Active	LiDAR		
[108]	Peatland	NA	<i>Sphagnum</i> spp., shrub.	Active	NIR & Thermal & LiDAR		
[109]	Bog	Disturbed	<i>Erica tetralix</i> , <i>Calluna vulgaris</i> , <i>Ericaceae</i> spp., <i>Eriophorum vaginatum</i> , <i>Trichophorum cespitosum</i> , <i>Cyperaceae</i> spp., <i>Sphagnum</i> spp.	Passive	RGB		
[99]	Peatland	Natural	<i>Caricetum appropinquatae</i> , <i>Caricetum gracilis</i> , <i>Glycerietum maximae</i> , <i>Phragmitetum australis</i> , alder, willow encroachments.,	Active	LiDAR		
[98]	Bog	Disturbed	<i>Gaultheria shallon</i> , <i>Pinus contorta</i> , <i>Tsuga heterophylla</i> , <i>Rhododendron groenlandicum</i> , <i>Sphagnum</i> spp.	Active	LiDAR		
[101]	NA	Disturbed	<i>Phragmites australis</i>	Active	NA		
[110]	Peatland	Disturbed	NA	Active	LiDAR		
[109]	Bog	Disturbed	<i>Erica tetralix</i> , <i>Calluna vulgaris</i> , <i>Ericaceae</i> spp., <i>Eriophorum vaginatum</i> , <i>Trichophorum cespitosum</i> , <i>Cyperaceae</i> spp., <i>Sphagnum</i> spp.	Passive	RGB		Peat estimation
[100]	Peatland	NA	<i>Sphagnum</i> spp., shrub.	Active	LiDAR		Peatland restoration
[111]	Peatland	Disturbed	<i>Populus tremuloides</i> , <i>Populus balsamifera</i> , <i>Betula papyrifera</i> , <i>Picea mariana</i> , <i>Pinus banksiana</i> , <i>Prunus virginiana</i> , <i>Alnus crispa</i> , <i>Amelanchier alnifolia</i> , <i>Symphoricarpos albus</i> , <i>Ledum groenlandicum</i> Oeder, <i>Betula pumila</i> , <i>Salix</i> spp.	Active	LiDAR	Peatland wildfire vulnerability and monitoring	
[26]	Peatland	Disturbed	<i>Populus tremuloides</i> , <i>Populus balsamifera</i> , <i>Picea glauca</i> , <i>P. mariana</i> , <i>Betula glandulosa</i> , <i>Rhododendron groenlandicum</i> , <i>Sphagnum</i> spp.	Active	LiDAR		
[103]	Peatland	NA	<i>Sphagnum</i> spp., <i>Typha angustifolia</i> , <i>Chamaedaphne calyculata</i> , <i>Rhododendron groenlandicum</i> , <i>Kalmia angustifolia</i> , <i>Vaccinium myrtilloides</i> , <i>Eriophorum vaginatum</i> , <i>Picea mariana</i> , <i>Betula populifolia</i> , <i>Larix laricina</i> .	Passive	Hyperspectral		
[112]	Bog	Natural	<i>Sphagnum</i> spp., vascular plants.	Passive	Hyperspectral	Hyperspectral validation/RS techniques and data analysis	
[113]	Fen	Natural	<i>Sphagnum</i> spp., <i>Eriophorum angustifolium</i> , <i>Carex</i> spp., <i>Oxycoccus palustris</i> , <i>Typha latifolia</i> ,	Passive	Hyperspectral		
[114]	Fen	Natural	<i>Sphagnum</i> spp., <i>Eriophorum angustifolium</i> , <i>Carex</i> spp., <i>Oxycoccus palustris</i> , <i>Typha latifolia</i> ,	Passive	Hyperspectral	Vegetation analysis and modelling	
[115]	Peatland	NA	<i>Eriophorum vaginatum</i>	Passive	Hyperspectral		

* Note: In this table, the term "peatland" is used comprehensively to refer to all peatlands considered in the study unless otherwise specified.

4.3. UAV-Based Remote Sensing

Remote sensing technologies, such as unmanned aerial vehicles (UAVs), have revolutionised environmental monitoring and management. In recent years, UAV-based remote sensing has gained prominence in peatland research due to its ability to provide high-resolution data for mapping and monitoring purposes (Table 5).

4.3.1. Mapping Carbon Fluxes and Stocks

An article by Ivanov et al. (2021) demonstrates the potential of UAV remote sensing for mapping CO₂ fluxes and carbon (C) stocks in peatland ecosystems. Their findings highlight the potential of UAV remote sensing for accurately assessing microform groups and estimating CO₂ fluxes [116]. Those findings are consistent with previous research by Beyer et al. (2019), who successfully mapped vegetation communities in rewetted fen sites using UAV-based multisensory data [117]. By exploring the potential use of aboveground vegetation characteristics as indicators for mapping below-ground C stocks in peatlands, they demonstrate that UAV remote sensing combined with structural equation modelling can improve the estimation of below-ground C stocks and our understanding of C dynamics in peatland ecosystems.

4.3.2. Monitoring of Peatland Hydrology

UAVs with thermal and multispectral sensors have shown promise in monitoring peatland hydrological dynamics [117]. By capturing images at different wavelengths, these sensors can detect fluctuations in soil moisture content and the levels of the water table. Such information is crucial for assessing peatland health, understanding hydrological processes, and informing land management decisions.

Hydrological processes in peatlands influence carbon cycling and overall ecosystem health. Studies by Lampert et al. (2020) and Ikkala et al. (2022) focus on monitoring hydrological impacts in peatland ecosystems using UAV remote sensing [118,119]. Lampert et al. (2020) investigated vertical mixing processes and boundary layer methane isotopy using UAV-based sampling to study spatial variability [119]. Ikkala et al. (2022) analysed elevation changes and flow paths in peatland restoration, highlighting the ability of UAV mapping to assess wetness and hydrological impacts. Therefore, they reveal the effectiveness of UAV remote sensing in studying spatial variability and capturing methane emissions [118].

Additionally, Scheller et al. (2022) studied UAV-based methane emission mapping in Arctic terrestrial ecosystems and demonstrated the potential of UAVs in capturing spatial variability and enhancing the research on methane dynamics in peatlands [120]. Ikkala et al. (2022) focus on monitoring the hydrological impacts of peatland restoration using UAV and LiDAR data. They demonstrate that UAV mapping can assess elevation changes, flow paths, and wetness, providing valuable insights into hydrological processes [118].

4.3.3. Assessing Vegetation Structure and Disturbance Impacts

Understanding vegetation structure and the impacts of disturbances is crucial for effective peatland management and conservation. Díaz-Varela et al. (2018) present a methodology for analysing vegetation structure in bog-heathland mosaics using UAV-based imagery [48]. Similarly, the study by Harris and Baird (2019) uses UAV-derived digital surface models to assist in understanding vegetation patterning in recovering blanket peatlands. Their study highlights the value of UAV remote sensing in characterizing complex wetland habitats [121]. Lovitt et al. (2018) evaluate the impacts of low-impact seismic lines on hydrology, methane emissions, and surface morphology in boreal treed bogs. They emphasise the significant impacts of disturbances on peatland ecosystems [32].

4.3.4. Limitations and Challenges

UAV-based remote sensing on peatlands has limitations—for instance, limited spatial and temporal coverage of UAV surveys. The study by Beyer et al. (2019) acknowledges that the extent of UAV mapping is limited compared to satellite-based systems, which can cover larger areas [117]. Similarly, Lendziuch et al. (2021) point out that their study focused on specific locations within a montane peat bog, limiting the generalizability of their findings [122]. The small footprint of UAV surveys and their reliance on favourable weather conditions also restrict the temporal coverage of data collection, as mentioned by Lampert et al. (2020) in [119].

The cost associated with UAV remote sensing can be a significant challenge. Scheller et al. (2022) highlight the cost and technical challenges of using high-precision trace gas analysers in UAV-based methane emission mapping [120]. Moreover, accessing remote and challenging peatland sites for data collection can be difficult, as Díaz-Varela et al. (2018) mentioned in their study on bog-heathland mosaics [48]. These limitations may hinder the widespread application of UAV remote sensing in peatland research.

The processing and analysis of large volumes of remote sensing data can be complex and time-consuming. The study by Ivanov et al. (2021) involves advanced data processing techniques, such as orthophoto plan compilation and structural equation modelling, which require expertise and computational resources [116]. Additionally, Díaz-Varela et al. (2018) mention the need for accurate georeferencing, image overlap, and external control data to ensure data quality and precise analysis [48].

The selection and integration of appropriate sensors and instruments pose technical challenges in UAV remote sensing. Arroyo-Mora et al. (2019) discuss the implementation of a UAV equipped with a hyperspectral system, highlighting the limitations of airborne hyperspectral remote sensing due to its relatively high cost and low temporal resolution compared to satellite platforms [13]. Furthermore, Ikkala et al. (2022) highlight the need for precise georeferencing and control data to ensure accurate elevation measurements using UAV Structure-From-Motion (SfM) [118].

Interpreting and validating UAV remote sensing data can be challenging. Harris and Baird (2019) discuss the importance of ground truth data and the limitations of vertical accuracy in their study on vegetation patterning in recovering blanket peatlands [121]. The authors emphasise the need for continued monitoring and validation of topography and morphology in self-restoring peatlands to enhance the understanding of revegetation processes. Lovitt et al. (2018) also mention the site-specific nature of relationships between vegetation proxies and below-ground C stocks, emphasising the need for further research to assess the generalizability of findings [32].

The relationships between vegetation attributes and C stocks are likely site-specific, depending on geographic location, species composition, and peatland status [123]. Generalising the findings across different landscapes requires further investigation and validation. Furthermore, due to the intricate nature of peatland ecosystems, it is imperative to employ advanced modelling techniques like support vector machines (SVMs) and random forests (RFs) [117,121,124] to effectively capture the complex interplay among canopy reflectance, vegetation attributes, and C gradient variations.

Table 5. UAV studies, instruments utilised and applications.

Reference	Peatland Type *	Peatland Status	Dominant Vegetation	UAV	Sensors	Spectral Range	Spatial Resolution	Indices/Products	Applications
[125]	Mire	Disturbed	<i>Betula nana</i> , <i>Empetrum hermaphroditum</i> , <i>Sphagnum</i> spp., <i>Carex</i> spp.	Robota fixed wing	Panasonic Lumix-GM1	RGB	>1 cm	RGB image	Cover classification map
[13]	Peatland	NA	<i>Phragmites australis</i>	Matrice 600 Pro	micro-Compact Airborne Spectrographic Imager (μ CASI)	401–996	5 cm	Digital Elevation Model (DEM)	Ecological monitoring
[124]	Bog	Disturbed	<i>Eriophorum</i> spp., <i>Calluna vulgaris</i> , <i>Sphagnum</i> spp.	Wingspan Fixed-Wing	Panasonic Lumix DMC-LX7	RGB	4.5 cm	RGB image	Mapping and ecological classification
[32]	Bog	Disturbed	<i>Picea mariana</i> , <i>Rhododendron groelandicum</i> , <i>Oxycoccus microcarpus</i> , <i>Salix</i> spp., <i>Sphagnum</i> spp.	Aeryon Skyranger	HDZoom30 RGB	RGB	2 cm	Digital Terrain Model (DTM)	Mapping microtopography and WTD
[122]	Bog	NA	<i>Sphagnum</i> spp., <i>Vaccinium myrtillus</i> , <i>Pinus mungo Turra</i>	Mavic Pro, MikroKopter ARF XL	FLIR DUO R dual-sensor RGB/thermal, Tetracam μ -MCA Snap 6	750–1350, 550–900	3 cm	RGB indices: RGI, VVI, VDVI, VARI, TGI, SI, SHP, SCI, SAT, NGRDI, NDTI, NDI, HI, GRVI, GLI, GLAI, ExG, ERGBVE, CI, BI, RI, HUE, Multispectral: NDVI	Mapping WTD
[47]	Bog	Disturbed	<i>Sphagnum</i> spp.	Aeryon Skyranger	Aeryon HDZoom30	RGB	2 cm	NA	
[120]	Fen	Natural	<i>Dupontia psilosantha</i> , <i>Eriophorum scheuchzeri</i>	Phantom 4 Pro	LI-COR LI-7810	NA	NA	NA	Methane emission mapping

Table 5. Cont.

Reference	Peatland Type *	Peatland Status	Dominant Vegetation	UAV	Sensors	Spectral Range	Spatial Resolution	Indices/Products	Applications
[126]	Peatland	Disturbed	Mosses, sedges, birch, spruce, pine	Fixed-Wing	Canon Powershot SX260, Canon Powershot S100, FLIR Tau 2 TC324 TIR	RGB	5 cm	BNDVI, NIRGB, TIR	Monitoring the functioning of a treatment peatland purifying mine process effluent water
[48]	Bog	NA	<i>Carex</i> spp., <i>Eriophorum angustifolium</i> , <i>Molinia caerulea</i> , <i>Sphagnum</i> spp., <i>Trichophorum cespitosum</i> , <i>Drosera rotundifolia</i> , <i>Juncus squarrosus</i> , <i>Potamogeton polygonifolius</i> , <i>Hypericum helodes</i> , <i>Parnassia palustris</i>	Microdrone MD4-1000	Olympus E-P1	RGB	2.53 cm	Band ratios: Blue/(Red+Blue+Green), Red/(Red+Blue brightness+Green), Green/(Red+Blue+Green), Mean difference to neighbors: Green Layer, DSM	Peatland classification
[23]	Bog	Disturbed	<i>Sphagnum</i> spp., <i>Chamaedaphne calyculata</i> , <i>Rhododendron groenlandicum</i> , <i>Kalmia angustifolia</i> , <i>Vaccinium myrtilloides</i> , <i>Picea mariana</i> , <i>Betula populifolia</i> , <i>Larix laricina</i>	Matrice 600 Pro	Canon DSLR (RGB), LiAIR S220 (LiDAR)		±2 cm	Point Cloud	
[116]	Bog	Disturbed	<i>Sphagnum cuspidatum</i> , <i>Odontoschisma fluitans</i> , <i>Drosera rotundifolia</i> , <i>Rhynchospora alba</i> , <i>Eriophorum vaginatum</i> , <i>Chamaedaphne calyculata</i> , <i>Andromeda polifolia</i> , <i>Rhododendron tomentosum</i> <i>Harmaja</i> , <i>Vaccinium oxycoccos</i>	Mavic 2 Pro	L1D-20c	RGB	2.4 cm	NA	Peatland mapping
[46]	Peatland	Disturbed	bushes, trees	Mavic Pro	RGB Built-in	RGB	1–3 cm	DSM	

Table 5. Cont.

Reference	Peatland Type *	Peatland Status	Dominant Vegetation	UAV	Sensors	Spectral Range	Spatial Resolution	Indices/Products	Applications
[127]	Peatland	Disturbed	tussocky microrelief	NA	NA	NA	NA	NA	Peatland monitoring
[128]	Peatland	Natural	NA	Matrice 210 v2	Zenmuse XT2	Thermal	NA	NA	
[119]	Peatland	Restored	NA	Quadrocopter ALICE	AMSYS 5812-0150-B, TSYS01, Humicap HMP110	NA	NA	NA	
[123]	Bog	Restored	<i>Sphagnum</i> spp., <i>Polytrichum strictum</i> , <i>Calluna vulgaris</i> , <i>Eriophorum vaginatum</i>	eBee SQ	Parrot Sequoia	440–850	4 cm	NDVI	Restoration Monitoring
[121]	Bog	Disturbed	<i>Calluna vulgaris</i> , <i>Eriophorum vaginatum</i> , <i>Eriophorum angustifolium</i> , <i>Sphagnum</i> spp.	SenseFly swingletCam	Canon IXUS 220 HS	RGB	Orhtophoto: 2.46 cm, DSM: 20 cm	DSM, Elevation Slope (ELEV SLP), Profile curvature (VCU), Plan curvature (HCU)	
[117]	Fen	Restored	<i>Carex</i> spp., <i>Epilobium hirsutum</i> , <i>Juncus effusus</i> , <i>Glyceria maxima</i> , <i>Agrostis stolonifera</i> , <i>Typha latifolia</i>	eBee Plus	RGB senseFly S.O.D.A., Sequoia multispectral, FLIR TAU 2 thermal	Multispectral: 550–790	RGB: 1.7–1.5, Multispectral: 7.6–7.9, Thermal: 15.1 cm	GI, NDVI, reNDVI, gNDVI	
[118]	Fen	Restored	<i>Papillosum</i> , <i>Sphagnum</i> spp.	Phantom 4 Pro/Phantom 4 RTK	RGB Built-in	RGB	1.2–3.33 cm	DTM	

* Note: In this table, the term “peatland” is used comprehensively to refer to all peatlands considered in the study unless otherwise specified.

4.4. In Situ-Based Remote Sensing

In situ remote sensing techniques have become increasingly valuable in peatland research, providing insights into various aspects of these ecosystems and mainly being used to validate the other measurements using different platforms. Regarding the commonly used sensors or instruments, the acquisition of canopy spectral reflectance in the field has primarily relied on proximal sensing using field spectrometers. This approach has been employed in approximately 75% of all conducted studies. Among the instruments utilised, the Analytical Spectral Devices (ASD, USA) series has emerged as the most used. These instruments operate within the spectral range of 350 to 2500 nm, as exemplified in various instances [129,130] (Table 6).

The potential of utilising the spectral data to distinguish between different Sphagnum species has been a subject of speculation in previous literature. Noted that they differ dramatically in laboratory and field measurements [131]. However, our understanding of intraspecific variation in the spectra of Sphagnum species remains limited. This knowledge gap is due to the relatively small sample sizes employed in prior studies, which often included only a single sample per species or a limited number of species under investigation. Additionally, it is worth noting that the bulk of recent studies investigating the spectral characteristics of Sphagnum, as conducted by Lees et al. (2020), have primarily focused on temperate peatlands [49]. This differs significantly from boreal peatlands, where growing conditions are markedly distinct due to factors such as the duration of the snow-free season and seasonal fluctuations in temperature and solar irradiance when compared to the temperate zone. Furthermore, many in situ peatland vegetation studies have employed sensors that solely capture data within the visible (VIS) and near-infrared (NIR) spectral regions [131–133]. Consequently, insights related to species identification and moisture content obtained through shortwave infrared (SWIR) wavelength data have not yet been thoroughly investigated in the context of boreal peatland vegetation.

Several studies [27,129,134] highlight the usefulness of in situ measurements in capturing plot-scale changes in peatland ecosystems. These techniques enable the detection of vegetation productivity, biodiversity, and degradation caused by human activities [135–137]. However, it is essential to note that remote sensing data may have limitations in accurately capturing fine-scale details and species-level information, which could be critical for understanding specific ecological dynamics within peatlands.

The assessment of peatland hydrology using remote sensing has been investigated by several researchers [130,133,135]. These studies demonstrate the potential of remote sensing in detecting changes in water table levels and hydrological patterns. Nevertheless, challenges exist in accurately capturing the complexities of peatland hydrology due to the presence of variable water levels and the influence of vegetation on the water regime. Moreover, it was noted that there was a lack of studies focusing on drought investigations despite the availability of the hyperspectral in situ data.

Several studies have focused on the relationship between spectral indices and peatland characteristics [27,50,137–139]. These investigations use spectral indices to estimate carbon content, vegetation cover, or ecosystem productivity. However, caution must be exercised in interpreting spectral indices, as multiple factors can influence them, including vegetation composition, atmospheric conditions, and sensor characteristics. Moreover, the transferability and generalizability of spectral indices across different peatland types and regions require further exploration.

Climate change impacts on peatland ecosystems have been examined in several studies [49,131,132,136]. These investigations shed light on shifts in vegetation communities, carbon and methane flux alterations, and peatland structure changes due to climate warming. However, it is essential to consider the complexities of climate-peatland interactions, including feedback mechanisms and the interplay of multiple environmental drivers, which may not be fully captured by remote sensing techniques alone.

Table 6. In situ studies, instruments utilised and applications.

Reference	Peatland Type *	Peatland Status	Dominant Vegetation	Instrument	Spectral Range	Indices	Applications
[49]	Bog	Near natural, restored	<i>Sphagnum</i> spp.	SVC HR-1024 spectroradiometer	350–2500	NDWI, NDVI, EVI, PRI, fWBI, C _{im}	Estimate water content and GPP
[139]	Fen	Natural	<i>Sphagnum</i> spp.	SKR1860	531–1240	NDVI, PRI, WBI, C _{igreen}	Assess the impact of manipulated environmental conditions on Sphagnum
[132]	Peatland	Disturbed	<i>Sphagnum</i> spp.	Decagon Inc, ASD	630 and 800	NDVI	Response of boreal peatland community composition and NDVI
[136]	Bog	Restored	White beak rush	AMSPEC-III	522–809	PRI	Seasonal changes in Light Use Efficiency (LUE)
[129]	Fen	NA	<i>Sphagnum</i> spp.	ASD Fieldspec	350–2500	WI, FWBI	Subsurface moisture and WTD monitoring
[130]	Bog	NA	NA	ASD Fieldspec	350–2500	NA	Classifying peatland vegetation
[140]	Bog	NA	<i>Sphagnum</i> spp.	“Spectra Vista Corporation (SVC) DC-R/T Integrating Sphere fitted to an HR-1024i spectroradiometer”	400–2400	NA	Investigation of nitrogen deposition
[27]	Bog	NA	NA	Riegl VZ-1000	NA	NA	Characterising peatland microtopography
[134]	Bog	Disturbed	NA	FARO Focus3D X330	NA	NA	Assessment of surface change in blanket bogs
[138]	Fen	Natural	NA	CM3 pyranometers, Quantum sensors	NA	NDVI	Net Ecosystem Productivity of peatland
[135]	Bog	Disturbed	<i>Sphagnum</i> spp.	Canon EOS 5D	RGB	NA	Tracking the plant phenology
[137]	Fen	Natural	<i>Carex acutiformis</i>	Spectral Reflectance Sensors	NA	NA	Above- and belowground phenology
[50]	Fen	Natural	<i>Sphagnum</i> spp.	Piccolo Doppio	400–1000	NDVI, EVI, NIR _v	Observing peatland vegetation dynamic
[131]	Peatland	Natural	<i>Sphagnum</i> spp.	ASD Fieldspec	350–2500	WI, FWBI, CI, NDVI	Explores the relationship between spectral indices and greenhouse gas emissions in northern peatland ecosystems
[133]	Fen	Natural	<i>Sphagnum</i> spp., wet brown mosses	ASD Fieldspec	325–1075	NA	Detect vegetation characteristics

* Note: in this table, the term “peatland” is used comprehensively to refer to all peatlands considered in the study unless otherwise specified.

4.5. Multiple Platforms

Incorporating ground-based measurements, field surveys, and integrating multiple data sources can enhance the accuracy and reliability of remote sensing-based assessments. Furthermore, interdisciplinary approaches that combine remote sensing with ecological modelling, biogeochemical analyses, and on-the-ground observations are essential to advance our understanding of peatland ecosystems and their responses to environmental changes. Table 7 includes the studies which combined multiple remote sensing platforms.

4.5.1. Vegetation Dynamics and Phenology

Several studies have explored using combined remote sensing platforms, data or measuring techniques to assess vegetation dynamics and phenology in peatland ecosystems [38,141,142]. Bhatnagar et al. (2021) present an innovative approach to monitoring wetlands, specifically emphasising ombrotrophic peatlands [143]. Their methodology combines machine learning algorithms, satellite data analysis and drone-RGB image processing to generate seasonality maps of vegetation communities across wetland areas [143]. Notably, the authors successfully demonstrate how a limited number of drone images can enhance satellite imagery, improving classification accuracy [143]. This proposed approach stands out as a robust, efficient, and cost-effective method for mapping wetland habitats [143]. However, it is worth noting that while the study offers valuable insights into wetland monitoring, its primary focus is on a particular type of peatland, potentially not accounting for the full range of peatland conditions [143].

Building upon the work of Bhatnagar et al. (2021) in [143], Räsänen et al. (2019, 2020) emphasised the importance of high-resolution imagery in mapping peatland vegetation [30,144]. They compared multiple optical remote-sensing data from satellite imagery, airborne and UAV, for mapping and detecting spatial patterns of vegetation properties in three northern peatland areas. The article highlights the rarity of a universal approach suitable for grouping and mapping peatland vegetation, as the diversity within peatland ecosystems often necessitates tailored methodologies. Therefore, the authors recommended some guidelines for mapping vegetation patterns in peatlands. They suggest that different methods and data sources should be tried and compared to find the best fit for each case and purpose. They also advise that various maps should show different vegetation features and their interactions. They emphasise that each map's strengths, weaknesses and uncertainties should be clearly stated [30,51].

Moreover, Arroyo-Mora et al. (2018) explored the potential of Sentinel-2A imagery for monitoring phenospectral dynamics, providing valuable insights into the phenological changes of peatland vegetation [141]. However, validation approaches using higher spatial and spectral resolution data, such as airborne hyperspectral imagery (HSI) and in situ measurements, are necessary to improve the accuracy of these satellite-based land products. That is what was concluded by the researchers who utilised three datasets: Sentinel-2A imagery, airborne hyperspectral imagery (HSI), and field spectra [141].

Millard and Richardson (2018) and Räsänen et al. (2020) also focus on vegetation phenology and biomass estimation in peatlands. These studies demonstrate the use of remote sensing data, including hyperspectral drone data and satellite imagery, to estimate vegetation indices, leaf-area index (LAI), and biomass. They emphasise the importance of considering vegetation heterogeneity and microtopographic features when modelling and upscaling peatland characteristics [51,77].

4.5.2. Biomass Estimation

Räsänen et al. (2020) demonstrated the potential of ultra-high-resolution remote sensing data, including hyperspectral drone data, in detecting peatland LAI and biomass patterns. They emphasised the importance of considering multiple remote sensing data sources and combining spectral, topographic, and structural information for accurate vegetation mapping [144]. Although hyperspectral imagery provided only slight benefits in analysing LAI and above-ground biomass patterns, combining spectral data with topo-

graphic and structural information is crucial for accurately mapping vegetation patterns in spatially heterogeneous landscapes like northern peatlands [144]. Metzger et al. (2017) highlighted the challenges and limitations of using vegetation indices as proxies for vegetation characteristics in temperate grassland fens, particularly in the context of varying management intensities. LAI was observed to have limited predictive capability for photosynthesis potential (PP) and biomass, as its estimation from NDVI proved inaccurate [38].

While NDVI was found to be a more reliable predictor of PP than LAI, applying NDVI as a proxy for LAI in photosynthesis models should be considered cautiously due to its high uncertainty. Further research and validation studies are needed to improve the understanding and modelling of carbon balance in peatlands [38].

4.5.3. Restoration Monitoring

Monitoring the success of peatland restoration projects is crucial for evaluating ecosystem recovery and carbon assimilation. Lees et al. (2021) modelled GPP through MODIS data and used a handheld spectrometer to obtain small-scale spectral data. They evaluated the models' reliability for estimating ecosystem photosynthesis in peatlands at different scales. The study aimed to identify the factors influencing GPP in peatland ecosystems and determine if large-scale models utilising satellite data can accurately estimate GPP at smaller scales by comparing the results with field measurements. Their findings showed that the model successfully estimated GPP from remotely sensed data at both small and large scales, and the estimates correlated well with the GPP measured using chamber and Eddy Covariance (EC) techniques.

Additionally, DeLancey et al. (2019) assessed the long-term monitoring capabilities of RADARSAT-2 and UAV imagery for tracking peatland restoration success over time [145]. Likewise, White et al. (2020) studied the potential use of RADARSAT-2 satellite and high-resolution UAV imagery for monitoring the restoration of peatlands. They suggested that RADARSAT-2 data with UAV imagery could be valuable for monitoring peatland restoration success over time despite acknowledging limitations in the study design [15].

4.5.4. Challenges and Future Directions

Validation of remote sensing-based estimations remains a challenge in peatland research. Arroyo-Mora et al. (2018) highlight the need for validation using higher-resolution data, such as airborne hyperspectral imagery (HSI), and in situ measurements to improve accuracy. This is crucial for ensuring reliable and precise estimation of peatland properties [141].

Metzger et al. (2017) emphasise the significance of interdisciplinary collaboration and knowledge integration for comprehensive peatland analysis. They emphasise incorporating ecological and hydrological knowledge with remote sensing technologies. Future research should focus on integrating multiple data sources, including environmental covariates and machine learning algorithms, to enhance the understanding and modelling of peatland ecosystems [38].

Additionally, future research should focus on refining multiple approaches and methodologies, improving calibration techniques, and integrating multi-sensor data to enhance our understanding of peatland ecosystems and their response to global environmental changes. We found that just a few studies have investigated the benefits of hyperspectral drone data compared to other datasets for analysing vegetation patterns in peatlands. Future studies should explore the potential benefits of hyperspectral UAV data in high-resolution estimation of vegetation features and patterns on peatlands. This exploration may enhance not only mapping of vegetation but also the monitoring of peatland restoration efforts.

Table 7. A summary of the multiple remote sensing platforms.

Reference	Peatland Type *	Peatland Status	Dominant Vegetation	Active/Passive	Spaceborne	Airborne	UAV	In Situ	Applications
[146]	Bog	Disturbed	Graminoid, <i>Ericaceae</i> spp., <i>Sphagnum</i> spp.	Active		•		•	Carbon stocks estimation
[147]	Peatland	Disturbed	<i>Sphagnum</i> spp., <i>Carex</i> spp., shrub	Passive		•		•	Characterising peatland plant composition
[148]	Fen	Natural	<i>Eriophorum vaginatum</i> , <i>Calluna vulgaris</i> and <i>Erica tetralix</i> , <i>Sphagnum</i> spp., <i>Rhynchospora alba</i> .	Passive			•	•	Ecosystem respiration modelling and upscaling
[16]	Bog	Disturbed	<i>Epilobietea angustifolia</i> , <i>Caricetum limosae</i> , <i>Molinio-Arrhenatheretea</i> , <i>Nardo-Callunetea</i>	Mixed	•	•			Evaluation of peat extraction
[141]	Bog	Natural	<i>Sphagnum</i> spp., <i>Typha latifolia</i>	Passive	•	•		•	Evaluation of phenospectral dynamics
[149]	Bog	Natural	<i>Sphagnum</i> spp., <i>Carex</i> spp., <i>Typha latifolia</i>	Passive	•		•		Measuring land surface albedo
[150]	Bog	Disturbed	<i>Picea abies</i> , <i>Pinus sylvestris</i> , <i>Betula pubescens</i>	Mixed	•	•			Methane flux measurements
[151]	Bog	Natural	<i>Sphagnum</i> spp.	Mixed		•	•	•	
[51]	Fen	Natural	<i>Sphagnum</i> spp., evergreen shrubs	Mixed	•	•	•		Peatland mapping
[152]	Peatland	Natural	<i>Betula pubescens</i> , forb and shrub species	Mixed	•	•			
[145]	Peatland	Natural	<i>Sphagnum</i> spp.	Mixed	•	•			
[18]	Bog	Natural	<i>Sphagnum</i> spp., <i>Typha angustifolia</i>	Passive	•	•			
[143]	Bog	Natural	<i>Sphagnum</i> spp.	Passive	•		•		
[22]	Bog	Natural	<i>Sphagnum</i> spp., <i>Pleurozium schreberi</i> , <i>Eriophorum</i> sp., <i>Trichophorum germanicum</i>	Active	•	•			Peatland monitoring
[153]	Fen	Disturbed	<i>Sphagnum fuscum</i> , <i>Empetrum nigrum</i> , <i>Andromeda polyfolia</i> , <i>Betula nana</i> , <i>Rubus chamaemorus</i> , <i>Carex</i> spp.	Mixed	•		•		
[38]	Fen	Natural	<i>Carex panicea</i> , <i>Anthoxanthum odoratum</i> , <i>Carex vesicaria</i> , <i>Poa trivialis</i> , <i>Alopecurus pratensis</i>	Passive	•			•	Peatland management monitoring

Table 7. Cont.

Reference	Peatland Type *	Peatland Status	Dominant Vegetation	Active/Passive	Spaceborne	Airborne	UAV	In Situ	Applications
[15]	Bog	Restored	<i>Sphagnum</i> spp.	Mixed	•		•		Restoration monitoring
[154]	Peatland	Disturbed	<i>Sphagnum</i> spp., <i>Picea mariana</i>	Mixed	•	•			Soil, moisture monitoring
[77]	Peatland	Disturbed	<i>Sphagnum</i> spp., <i>Picea mariana</i>	Active	•	•			
[155]	Bog	Disturbed	<i>Sphagnum</i> spp.	Mixed		•	•		WTD monitoring
[156]	Bog	Restored	<i>Calluna vulgaris</i> , <i>Eriophorum angustifolium</i> , <i>Cladonia portentosa</i> , <i>Sphagnum capillifolium</i> , <i>Pleurozium schreberi</i> , <i>Trichiophorum germanicum</i>	Passive	•			•	Upscaling peatland productivity
[144]	Fen	Natural	<i>Sphagnum</i> spp.	Mixed	•	•	•		Vegetation mapping
[30]	Fen	Natural	Dwarf shrub, brown moss	Mixed	•	•	•		
[28]	Fen	Natural	Dwarf shrub, brown moss	Mixed	•	•	•		
[142]	Peatland	Natural	<i>Carex</i> spp., <i>Menyanthes trifoliata</i> , <i>Andromeda polifolia</i> , <i>Betula nana</i> , <i>Vaccinium oxycoccos</i> , <i>Sphagnum</i> spp., <i>B. pubescens</i> , <i>Pinus sylvestris</i>	Passive	•			•	Vegetation phenology monitoring

* Note: In this table, the term “peatland” is used comprehensively to refer to all peatlands considered in the study unless otherwise specified. Remote sensing platform differences in northern peatlands. The symbol • in this table is used to signify the Remote Sensing platforms employed in the study.

5. Comparison of Remote Sensing Platforms applications in Northern Peatlands

It has been perceived as a remarkable remote sensing platform usage shift over the past six years. Table 8 details the proportion of studies and applications of different remote sensing platforms applied in northern peatlands. Satellites, the traditional core of peatland remote sensing, continue to dominate, accounting for 36.5% of studies. This prevalence is attributed to the widespread availability of satellite imagery with high spatial and temporal resolution, enabling efficient mapping and monitoring of extensive peatland areas. Satellites offer cost-effective, large-scale data acquisition, making them ideal for large-scale peatland assessments and monitoring programs.

Table 8. Proportion of studies on each remote sensing platform and their applications areas in northern peatlands.

Platform	Proportion of Studies	Applications
Satellite	36.5%	Carbon and methane flux estimation (14%), fire dynamics monitoring (6%), hydrology (14%), mapping and monitoring peatland extent (42%), peatland degradation (4%), restoration and management monitoring (10%), vegetation assessment (10%)
Airborne	20.4%	Carbon and methane flux estimation (14%), fire dynamics monitoring (14%), hydrology (14%), mapping and monitoring peatland extent (36%), Other (7%), peatland degradation (0%), restoration and management monitoring (4%), vegetation assessment (11%)
UAV	13.9%	Carbon and methane flux estimation (11%), fire dynamics monitoring (0%), hydrology (11%), mapping and monitoring peatland extent (37%), peatland degradation (0%), restoration and management monitoring (37%), vegetation assessment (5%)
In situ	10.9%	Carbon and methane flux estimation (20%), fire dynamics monitoring (0%), hydrology (7%), mapping and monitoring peatland extent (13%), peatland degradation (0%), restoration and management monitoring (0%), vegetation assessment (60%)
Mixed	18.2%	Carbon and methane flux estimation (12%), fire dynamics monitoring (0%), hydrology (12%), mapping and monitoring peatland extent (40%), other (4%), peatland degradation (4%), restoration and management monitoring (8%), vegetation assessment (20%)

Nevertheless, their dominance has been challenged by the ascendancy of airborne sensors, which provide higher-resolution imagery, accounting for 20.4% of studies. This utilisation stems from their ability to capture finer details of peatland landscapes, enabling more detailed assessments of vegetation characteristics, land cover, and hydrological patterns. However, the higher operational costs of airborne sensors limit their widespread adoption compared to satellites. Speaking of ultra-high-resolution UAVs, despite their relatively recent development, they have experienced a remarkable rise in popularity, their usage increasing since 2017, accounting for 13.9%. In contrast, in situ sensors, while offering the finest resolution data, remain a niche technology employed in just 11% of studies. Mixed platforms offer a more comprehensive understanding of peatland features by fusing data from disparate sensors, e.g., satellite, airborne, UAV, and in situ, representing a promising approach enabling researchers to gain previously inaccessible insights. They account for 18% of studies. In situ and mixed remote sensing platforms have been used less than satellite and airborne platforms. This is primarily due to their higher cost and logistical complexity. In situ sensors require direct contact with the peatland surface, limiting their applicability to large-scale assessments (raw data extracted from the included articles for this section is in Supplementary Tables S2 and S3).

Figure 4 provides valuable insights into the evolution of research trends from 2017 to 2022 and can guide future research directions. Showing up the trend analysis of the applications over the years, the most common applications of remote sensing for northern peatlands are mapping and monitoring peatland in satellite, mixed and UAV, where it is increasing since 2017, while in airborne and in situ the increasing application is hydrol-

ogy and vegetation, respectively, notably that UAVs are emerging as a popular tool for restoration and management monitoring purposes. There is an observable gap in studies concentrating on peatland degradation. This area remains underexplored across all platforms, with no studies conducted utilising the airborne, UAV and in situ platforms. Fire dynamics monitoring is another underexplored area, with no studies conducted using the UAV and mixed platforms. There has been a growing interest in using remote sensing to assess carbon fluxes in peatlands, but this is still a relatively unexplored area of research utilising most of the platforms rather than satellites (raw data extracted from the included articles for this section is in the Supplementary Tables S4–S8).

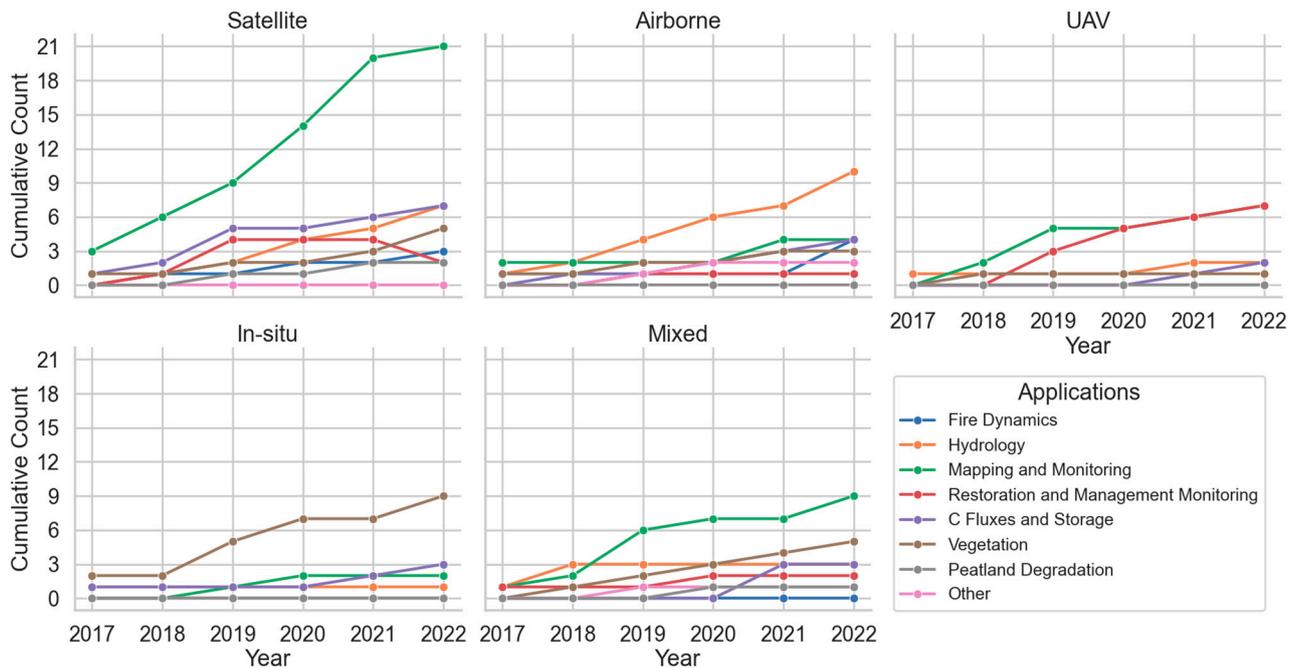


Figure 4. Year-to-year comparison between the applications of various remote sensing platforms in northern peatlands from 2017 to 2022 (the applications were aggregated based on the grouping themes in Supplementary Table S1).

6. Conclusions

Remote sensing approaches hold immense potential to contribute to northern peatlands by providing objective, continuous, and up-to-date information over different scales, from small to large spatial extents (ground-based, UAV, airborne, and satellite remote sensing data from optical, laser, and radar sensors). This paper reviews past and current remote sensing platforms utilised in peatland management. Moreover, it is highlighted that remote sensing has benefits as well as drawbacks, and we endorse a combined approach that employs multiple platforms and techniques to investigate the complexities of peatlands.

The following are the benefits of using remote sensing platforms in peatlands:

- Remote sensing, especially satellite, allows coverage of inaccessible terrain, providing a means to explore and monitor peatland areas that are difficult to access on foot or by traditional field measurements;
- It enables measurements and observations without direct contact with the studied object. This ensures that the physical properties of the peatland are not altered during data collection;
- Remote sensing facilitates upscaling from point scale measurements to larger scales, such as slopes, basins, valleys, or even entire mountain ranges. This capability allows a broader understanding of peatland dynamics and patterns across different spatial extents;

- Radar data, commonly used in remote sensing, provides weather independence. Data acquisition can continue regardless of weather conditions, allowing for consistent monitoring and analysis;
- Remote sensing enables the collection of complete and continuous data records over time from specific locations. This longitudinal data can reveal temporal patterns, changes, and trends in peatland characteristics and dynamics;
- Different sensors can be utilised in remote sensing, each capable of measuring specific physical properties of peatlands. This multi-sensor approach comprehensively explains various aspects, such as vegetation dynamics, hydrological conditions, and subsurface characteristics;
- Remote sensing data archives offer the opportunity to access historical data, allowing researchers to analyse peatland changes over time. By utilising these archives, valuable insights can be gained into long-term trends and transformations.
- The limitations associated with remote sensing in peatland research are as follows:
- Mapping peatland ecological conditions at the appropriate scale is challenging, as peatlands can appear visually homogeneous at moderate spatial resolutions, e.g., in satellite imageries such as MODIS, but display high complexity at finer resolutions, e.g., in drone and airborne imageries;
- The reflectance spectra of peatland vegetation, particularly Sphagnum mosses, can change when the mosses are desiccated, making it challenging to identify species and moisture content accurately using spectral satellite data;
- A comparably small number of studies have proven the concept of using hyperspectral satellite and UAV hyperspectral remote sensing data for peatland research. This indicates a need for further research to establish the effectiveness of remote sensing in this context;
- Acquiring very high spatial resolution remote sensing data can be expensive. The costs of obtaining such data may limit its accessibility and utilisation in peatland research and management applications;
- Remote sensing data with very high spatial resolution typically covers a small swath, resulting in limited coverage of peatland areas. This constraint can hinder the comprehensive assessment and monitoring of more significant peatland regions;
- The temporal resolution of most sensor systems is currently insufficient for practical peatland analysis. The frequency at which data is collected may not adequately capture the temporal dynamics and changes occurring within peatlands;
- In an operational context, where large volumes of data are involved, automated algorithms for peatland analysis become necessary. However, the existing algorithms are primarily designed for optical data, and there is a scarcity of studies focusing on radar data for peatland analysis;
- There is limited availability of field validation data, particularly in inaccessible areas. This limitation hampers the validation and verification of remote sensing-based peatland analysis methods, impeding the reliability of the results;
- Another limitation is the lack of quantitative error assessment methods for manual and automated peatland analysis using remote sensing. Establishing robust measures to assess the accuracy and uncertainty of remote sensing data-derived peatland information is crucial for ensuring the reliability and validity of the findings.

Perspectives for Future Research

Future directions for remote sensing in peatland research and management involve refining approaches and methodologies, improving calibration techniques, and integrating multi-sensor data. The review highlights the need for validation using higher-resolution data, such as satellite and airborne hyperspectral imagery, and in situ measurements to improve the accuracy of remote sensing-based estimations. Incorporating environmental covariates and machine learning algorithms and considering the complexities of peatland ecosystems are crucial for advancing our understanding and modelling of these unique en-

vironments. Additionally, further research is needed to address the limitations identified in the review, such as limited spatial and temporal coverage, cost constraints, data processing complexity, sensor selection, interpretation, and validation challenges. Finally, the review underscores the need to explore underutilised applications like peatland degradation and fire dynamics monitoring further to strengthen our understanding of northern peatland dynamics during environmental changes.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/rs16030591/s1>, Supplementary Table S1: List of the applications and grouping themes in the systematic literature search for review (for Figure 4); Supplementary Table S2: The total number and percentage of studies that used different remote sensing platforms (such as satellites, airborne, in situ, or mixed sensors) in northern peatlands over the years 2017–2022; Supplementary Table S3: The total number and percentage of studies that applied remote sensing-based applications in northern peatlands over the years 2017–2022; Supplementary Table S4: The total number and percentage of studies that used satellite included in the SLR over the years 2017–2022; Supplementary Table S5: The total number and percentage of studies that used airborne included in the SLR over the years 2017–2022; Supplementary Table S6: The total number and percentage of studies that used UAV included in the SLR over the years 2017–2022; Supplementary Table S7: The total number and percentage of studies that used in situ included in the SLR over the years 2017–2022; Supplementary Table S8: The total number and percentage of studies that used mixed or multiple platforms included in the SLR over the years 2017–2022.

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