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Review

Remote sensing applications for monitoring restoration outcomes in boreal forestry-drained peatlands - Reviewed applications and future potential

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A R T I C L E I N F O

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A B S T R A C T

Peatland restoration can halt biodiversity loss and organic soil degradation and mitigate climate change. Monitoring of restoration impacts requires novel approaches that can be scaled to large site networks. On a smaller scale, the restoration practitioners would likewise benefit from spatially and temporally comprehensive and objective monitoring data. This narrative review compiles potential remote sensing methods for practical monitoring of the ecohydrological processes in restoration of forestry-drained boreal peatlands to support and complement conventional ground monitoring approaches that are restricted by spatial coverage. Remote sensing provides tools for tracking the changes in soil surface moisture, water flow routes, vegetation cover and structure, topography, peat depth and greenhouse gas emissions. We emphasize that the suitable indicators of restoration success, platforms and sensors should be tailored to specific restoration cases with their own initial site conditions and restoration targets. The choice of spatial and temporal resolutions of data is defined by the scale and change rate of the restoration indicators. Data acquisition campaigns and selection of existing datasets require meticulous planning due to seasonal changes in hydrology and vegetation. We also compiled practical experiences on selecting remote sensing tools and ensuring satisfactory data quality to facilitate the implementation of remote-sensing-based monitoring. Finally, we provide recommendations on how the rapid development of remote sensing technology, encompassing new uncrewed applications and novel sensors on conventional platforms, can offer a range of monitoring tools to cater to the growing needs for spatially comprehensive data amounts assessing peatland restoration success in boreal conditions.

1. Introduction

Boreal peatlands, divided into bogs and fens as the primary types distinguished by their hydrology, are terrestrial ecosystems where net primary production exceeded decomposition, resulting in the long-term accumulation of partly decomposed organic matter (Wieder et al.,

Abbreviations: DSM, Digital Surface Model; DTM, Digital Terrain Model; FAO, Food and Agriculture Organization; GHG, Greenhouse Gas; GPR, Ground-Penetrating Radar; GPP, Gross Primary Productivity; GSD, Ground Sampling Distance; GW, Groundwater; InSAR, Interferometric Synthetic Aperture Radar; LiDAR, Light Detection and Ranging; NIR, Near-infrared; RGB, Red-Green-Blue; RS, Remote Sensing; SAR, Synthetic Aperture Radar; SfM, Structure-from-Motion; SWIR, Short-wave Infrared; TIR, Thermal Infrared; TOTRAM, Thermal-Optical Trapezoid Model; UAS, Uncrewed Aircraft System; VI, Vegetation Index; WT, Water Table.

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2006). Mires, more specifically, are peatlands where active peat formation continues (Joosten and Clarke, 2002). However, extensive drainage of boreal peatlands, especially for forestry, has caused a significant decline of biodiversity (Chapman et al., 2003) and disruption of ecosystem services (Harris et al., 2020; Leifeld and Menichetti, 2018; Page and Baird, 2016). Globally, around 51 Mha of total 463 Mha peatlands have been degraded contributing up to 3.4 Gt CO_2-eq emissions annually (Leifeld and Menichetti, 2018). Peatland restoration has emerged as a key nature-based solution for enhancing biodiversity and reviving essential ecosystem services such as carbon sequestration, water purification, and hydrological regulation (Günther et al., 2020; Haapalehto et al., 2011, 2014; Kareksela et al., 2015; Laine et al., 2019). Restoration efforts are being scaled up in various countries (Cris et al., 2014) to meet both climate and biodiversity goals, aligning with major policy frameworks such as United Nations Framework Convention on Climate Change, the European Union Habitats Directive, Biodiversity strategy 2030 and upcoming EU Restoration Law (European Union, 2021, 2022; Food and Agriculture Organization (FAO), 2020). Achieving the Paris agreement targets related to peatlands will require restoring almost 2 Mha of degraded peatlands annually (Sirin et al., 2020). Recognizing this urgency, the United Nations declared 2021–2030 as the Decade of Ecosystem Restoration; a global initiative to accelerate efforts to reverse ecological degradation, combat climate change, secure food and water supplies, improve public health, and boost sustainable economies (Gann et al., 2019). At the same time, there is growing recognition of the need to better assess restoration success, refine technical measures, and optimize the restoration approaches to ensure long-term outcomes (González et al., 2013; Mahmood and Strack, 2011; Martin-Ortega et al., 2014; Suding, 2011).

Peatlands have been drained for various land uses such as agriculture and peat extraction, and particularly in the boreal region, for forestry to enable or enhance tree growth (Nieminen et al., 2018). Drainage lowers the water table (WT) and increases the water flow rates, altering peatland hydrological function, vegetation composition, peat properties, peatland structure, and greenhouse gas (GHG) balance (Holden et al., 2004; Pitkänen et al., 2013; Waddington et al., 2014). In forestry-drained peatlands, the changes are more subtle than in the peatlands under more intensive land uses, yet there is a succession towards drier forest vegetation. Drainage for forestry, harvesting and fertilization also cause nutrient and sediment transports deteriorating the water quality in the downstream catchment (Nieminen et al., 2018). In contrast, rewetting as a restoration method aims to recover peatland hydrological functions, including water flow routes and velocities, water retention, WT depth, surface moisture, and groundwater (GW) connections to halt carbon mineralization and sustain peatland vegetation (Bechtold et al., 2018; Harvey et al., 2019; Menberu et al., 2016; Similä et al., 2014). The restoration usually causes temporary release of nutrients and organic matter in the downstream catchment due to the mobilization of peat mineralized during the drainage phase, but it appears to diminish during 5–10 years after the restoration (Ikkala and Similä, 2024). Rewetting initiates an inversed vegetation succession towards hydrophilic species and reinstates organic matter accumulation (Haapalehto et al., 2017; Laine et al., 2011). The resulting WT raise saturates the root zone, inhibiting tree growth (Smiljanić et al., 2014). The removal of trees is a typical part of restoring forestry-drained sites aiming at an original open landscape, reduced evapotranspiration, and increased light availability demanded by many pioneer species (Fig. 1; Similä et al., 2014). The subsequent secondary succession towards a peat-forming plant community promotes long-term carbon sequestration and storage (Wilson et al., 2016). While rewetting immediately reduces the CO_2 emissions, it may also lead to increased CH_4 emissions (Ojanen and Minkkinen, 2020). The carbon storage in the tree stand biomass also needs to be considered in the restoration planning, and in most of the cases, the sites have more trees after restoration than in the pristine state. Although restoration may not always recover the original natural state, it can help ecosystems reverse degradation, regain ecological functionality and improve their productivity and capacity to meet the needs of society (United Nations, 2021).

Peatlands in general have high spatial variability concerning peatland soil properties (Page and Baird, 2016), hydrological conditions

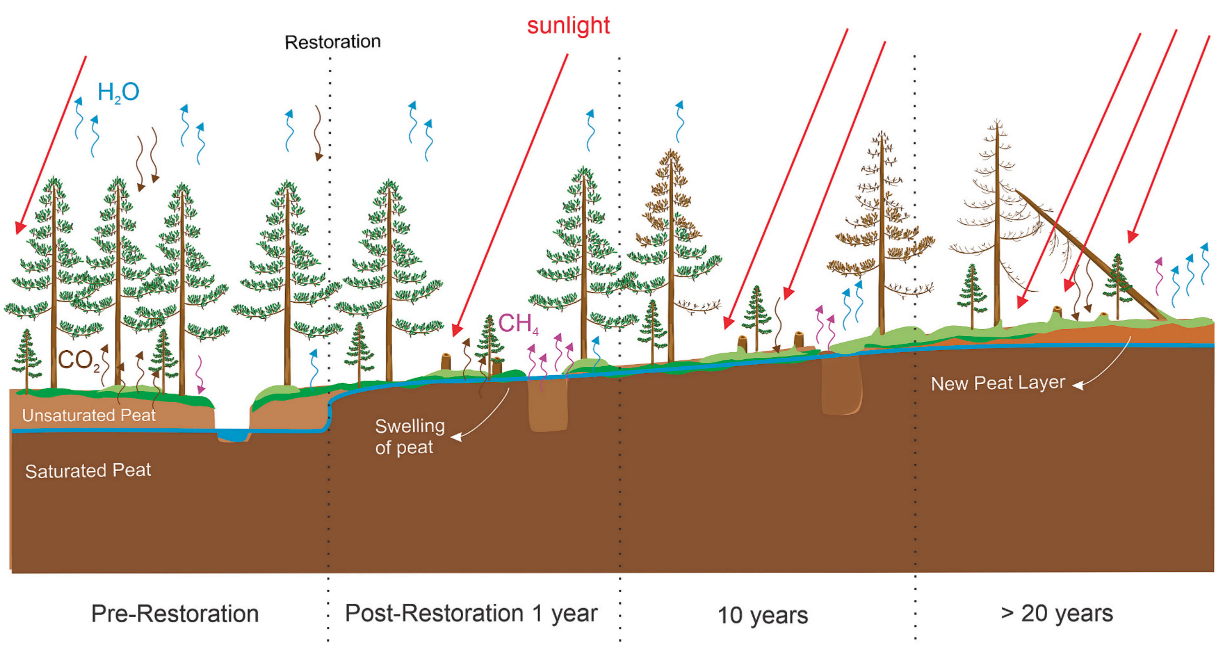

Fig. 1. Changes in evapotranspiration (H_2O blue arrows), sunlight availability (magnitude expressed via the number of red arrows), water table level, peat swelling and accumulation as well as greenhouse gas emissions (CO_2 brown and CH_4 purple arrows) in the restoration stages of a forestry-drained peatland site. The increased tree growth after drainage has caused increased evapotranspiration and decreased sunlight availability in the ground and field layer. Rewetting ends the subsidence, initiates peat swelling and carbon sequestration at the expense of increased methanogenesis. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

(Holden, 2005; Holden et al., 2011), vegetation cover (Alekseychik et al., 2021; Korrensalo et al., 2019), and GHG exchange (Griffiths et al., 2017; Zhang et al., 2020). In forestry-drained peatlands undergoing restoration, changes in WT, vegetation recovery, and water chemistry often follow spatial patterns related to proximity to filled ditches (Haapalehto et al., 2014, 2017). Despite the spatial patterns, restoration success has traditionally been assessed through sparse manual field observations such as standpipe wells for WT (Menberu et al., 2018; Shantz and Price, 2006) and permanent vegetation plots tracking plant community shift (Bonnett et al., 2009; Cris et al., 2014; D'Astous et al., 2013; Elo et al., 2024; Haapalehto et al., 2014, 2017). While these methods provide reliable field data, they capture only point-specific information, failing to account for broader spatial variability (Glenk and Martin-Ortega, 2018). Additionally, field-based monitoring is often impractical in remote areas, limiting its applicability to large-scale restoration efforts (Tehrany et al., 2017).

The practical limitations of the conventional field-based methods have created a clear need for remote sensing (RS) approaches capable of monitoring changes across large, often inaccessible areas with adequate spatial and temporal resolution (FAO, 2020; Minasny et al., 2019). While RS applications have been reviewed in the contexts of pristine and managed peatlands and wetlands, forests, hydrology, and restoration ecology more broadly (See the references in Table 1), a focused synthesis addressing RS use specially in peatland restoration monitoring is still lacking. To address the gap, this review aims to present a comprehensive overview of restoration success indicators and the remote sensing methods — both established and emerging — that are suitable for tracking restoration outcomes in boreal forestry-drained peatlands. These ecosystems, typically large and remote, are highly degraded yet represent a major opportunity for achieving large-scale restoration targets. At the same time, their size and heterogeneity pose significant challenges for monitoring and impact evaluation. To support effective implementation, we further provide recommendations for the practical use of RS in peatland restoration and identify key areas for which further methodological development and research are needed.

2. Review approach

To guide and structure this review, we formulated a set of peatland restoration success indicators (Table 2; Section 3) by adapting the general ecological restoration attributes proposed by Clewell et al. (2004) to the context of peatland-specific processes and characteristics. Besides considering the ecosystem community, integrity, connectivity, functions, resilience and self-sustainability, the attributes emphasize the importance of the abiotic factors as enablers of the biotic recovery. In peatland restoration, the primary intention is to recover the physical environment through rewetting, enabling ecosystem stability or development along the desired trajectory (Clewell et al., 2004, Attribute 4), and to integrate the site into the catchment hydrology (Attribute 6). Subsequently, restoration aims to recover local and landscape-level biotic components (succession towards a target community) and the associated abiotic processes, such as organic soil formation and carbon sequestration (Attributes 1–9). The degradation and restoration processes specific to boreal forestry-drained peatlands were considered based on the restoration framework presented by Similä et al. (2014). Using the defined restoration indicators as a foundation, we identified and selected the focal RS subjects, ensuring that each is directly linked to at least one indicator. In addition to assessing the ecohydrological recovery systematically, we also highlight applications of RS in supporting practical restoration monitoring.

Instead of a systematic protocol with all-encompassing literature analysis, we conducted a narrative review of the RS methods with potential for peatland restoration monitoring. Despite the narrativity, we aimed to provide a comprehensive overview of the selected topic. Thus, we performed systematic searches for ensuring the inclusion of all relevant literature. We searched for research papers using the query

Table 1
Previous review papers from different environments supporting the remote sensing (RS) of peatland restoration monitoring.

Category	Environment	Subject	Reference
Peatlands	Northern peatlands	Challenges and limitations of RS Applications	Abdelmajeed and Juszczak, 2024
	Peatlands	RS data applications	Czapiewski and Szumińska, 2022
	Temperate and boreal peatlands	The potentials, gaps, and challenges of RS of degradation	de Waard et al., 2024
	Peatlands	Mapping and monitoring	FAO, 2020
	Peatlands	Monitoring through multisource RS: optical and radar data applications	Ghazaryan et al., 2024
	Northern peatlands	Potential for using RS to estimate carbon fluxes	Lees et al., 2018
	Peatlands	Digital mapping	Minasny et al., 2019
	Peatlands	Mapping and monitoring conditions from global to field scale	Minasny et al., 2024
	Peatlands	Decision making for management and rehabilitation using information on water chemistry, hydrology, policy, and emerging monitoring methods	Monteverde et al., 2022
Wetlands	Wetlands	Multispectral and hyperspectral RS for identification and mapping of vegetation	Adam et al., 2010
	Boreal wetlands	RS data use for policy and management, evaluating ecosystem state and drivers of change	Chasmer et al., 2020a, 2020b
	Wetlands	UAS opportunities, technology and data	Dronova et al., 2021
	Wetlands	RS	Guo et al., 2017
	Wetlands	RS to select and monitor restoration sites	Klemas, 2013
	Wetlands	WT level monitoring using InSAR	Mohammadimanesh et al., 2018
Hydrology	Hydrological environments	Advances in soil moisture retrieval from SAR and hydrological applications	Kornelsen and Coulibalya, 2013
	Hydrological environments	RS	Schmugge et al., 2002
	Hydrological environments	Satellite RS applications for surface soil moisture monitoring	Wang and Qu, 2009
Ecosystems	Ecosystems	RS to assess biodiversity	Nagendra, 2001
	Degraded, damaged, transformed and destroyed ecosystems	RS for restoration ecology	Reif and Theel, 2016
	Ecosystems	Multispectral and radar satellite imagery to inform biodiversity monitoring, ecological research and conservation science	Schulte to Bühne and Pettorelli, 2018
	Ecosystems	Evaluating ecological restoration success	Wortley et al., 2013

(*continued on next page*)

Table 1 (*continued*)

Category	Environment	Subject	Reference
Forests	Terrestrial woody and herbaceous vegetation ecosystems	LiDAR and radar spaceborne RS of vegetation 3D structure for biodiversity and habitat	Bergen et al., 2009
	Forests	Opportunities, challenges, and future directions of digital aerial photogrammetry for updating area-based forest inventories	Goodbody et al., 2019
	Forests	SfM photogrammetry in forestry	Iglhaut et al., 2019
	Forests	Understanding forest health with RS spectral traits, processes, characteristics, approaches and data models	Lausch et al., 2016, 2017
	Boreal forests	RS of boreal forest biophysical and inventory parameters	Lutz et al., 2008
	Forests	RS technologies for enhancing forest inventories	White et al., 2016

("remotely sensed" OR "remote sensing" OR uav OR drone OR uas OR "satellite image" OR "aerial image*") AND (restoration) AND (peatland)* in Scopus and Web of Science on June 16, 2025. In total, 80 results were studied to initially exclude papers other than from boreal forestry-drained sites. Also, irrelevant studies due to their scope or lack of focus on monitoring were excluded. Only 11 relevant results remained after the exclusions. In addition to the articles found with the search strings, we added other relevant papers based on article references, our existing knowledge, and additional literature searches. We primarily included only such RS studies that utilized data collected with flying platforms, i.e., spaceborne and crewed and uncrewed airborne platforms, but included some examples of ground-based approaches when it was relevant. We excluded studies attempting to monitor fauna or its habitats with RS (see more in Dronova et al., 2021). To the best of our knowledge, we included all studies that have used RS monitoring methods in boreal forestry-drained peatland restoration.

As this set of papers was relatively limited and did not cover all potential RS methods, we included other RS studies from peatlands in other land uses and climate regions and other relevant environments with the main aim of showcasing such RS methods that could be used in peatland restoration monitoring. However, we acknowledge that there may be biases in the selection of literature with a narrative approach. In general, RS methods are independent of the site type and location. However, different site conditions, dense tree cover above all, might distract the methods on forestry-drained peatlands. Thus, the reader is recommended to continuously regard the site types of the cited papers (Tables 3–7) and bear in mind that research might not yet have revealed all site-specific challenges. We still recommend trialing the potential methods on boreal forestry-drained sites, and across different peatland types, land uses and climate zones. Furthermore, this paper introduces data models and other technical details at a very general level, and thus, we encourage the reader to find more details in the cited literature. Eventually, the narrative review included 151 original RS papers (Tables 3–7), 30 review papers (Table 1) and some technical reports.

In the following Section 3, we elaborate and justify the chosen restoration success indicators, and their conventional field-based monitoring approaches. In Section 4, we then list both potential and previously trialled RS methods for monitoring the indicators, while in Section 5, we discuss different sensors and platforms, quality management and limitations of RS approaches, and future development possibilities.

Table 2
Indicators and their aimed status reflecting peatland restoration success by category, conventional systematic monitoring approaches and potential RS monitoring subjects.

Category	Aimed indicator status	Conventional systematic monitoring approaches	Potential monitoring subjects assessed with RS
Hydrology	Raised WT level, recovered WT level dynamics and its variability	Manual standpipe well observations, WT level loggers	Open water cover, soil surface moisture
	Recovered surface water and GW flow paths and ponding	Manual standpipe well observations, WT level loggers, topographical surveys	(Micro) topography, open water cover, soil surface moisture
	Recovered GW disharge patterns	Stable water isotopes and other environmental tracers, manual water temperature measurements, fibre-optic sensing, handheld thermal cameras	Thermal anomalies
	Recovered water flow dynamics in the rivers and lakes downslope*	Staff gauges, water level loggers flow meters	Water cover, flow velocity
	Recovered water quality in the rivers and lakes downslope*	Water quality sampling, Secchi disk for turbidity and colour	Water turbidy and colour
Vegetation	Recovered field and ground layer vegetation community composition and structure	Permanent vegetation plots, vegetation type mapping	Ground and field layer vegetation cover, plant functional traits, vegetation structure
	Recovered tree stand structure	Tree trunk count, diameter, basal area and volume, canopy cover	Seedling, growth of trees, tree diameter distribution, deterioration and decease of trees
Peat	Recovered peat formation	Coring, GPR, *Sphagnum* growth measurements	Peat depth and structure
	Discontinued subsidence	Subsidence poles, topographical surveys	(Micro) topography, peat depth
	Discontinued peat degradation and recovered microtopography	Coring, subsidence poles, topographical surveys	(Micro) topography, peat quality
	Recovered GHG exchange balance	Eddy covariance and chamber GHG exchange measurements	GHG proxies, probing

[*] Typically observed outside the peatland site. This paper focuses on the indicators observed at the site.

3. Peatland restoration success indicators and their conventional monitoring

The main prerequisite for successful restoration is the re-establishment of hydrological conditions closer to pristine conditions, as hydrology underpins all major ecological processes in peatlands (Page and Baird, 2016). Key hydrological variables systematically monitored at the peatland restoration site include WT, or its opposite number relative to the soil surface level, i.e., WT depth, and its fluctuation, and soil moisture (Similä et al., 2014). As direct monitoring of pore water quality using RS is practically unfeasible, this review focuses on surface wetness and flow paths. Restoration interventions, such as ditch blocking, embankments, and dams, aim to slow down and disperse water flow (Similä et al., 2014). However, an ongoing challenge in restoration is that water flow paths often concentrate in subsided ditch surroundings while the area between ditches remains dry (Haapalehto et al., 2011; Ikkala et al., 2022; Tolvanen et al., 2020). Additionally, restoration can create unintended inundated areas, including (i) hollows from excavation of pits used for ditch blocking, (ii) pools forming behind dam construction, and (iii) depressions caused by restoration machinery (Similä et al., 2014).

WT levels have traditionally been recorded either manually (Laine et al., 2011) or with automated water level loggers (Menberu et al., 2016; Shantz and Price, 2006). Direct WT measurements with RS are usually not possible since the saturated zone is usually hidden by a layer of soil that obstructs electromagnetic waves used for sensing (Schmugge et al., 2002). However, the soil surface moisture may enable indirect estimation of WT depth if a relationship is well defined for soil cover (Bechtold et al., 2018; Kalacska et al., 2018). Soil surface moisture has also been monitored directly by taking samples for drying and weighing in the laboratory (Ikkala et al., 2022) or using handheld moisture sensors (Takada et al., 2009). For identifying subsoil water flow paths, there are not many systematic ground-based methods. Approximate directions can be estimated when WT distribution relative to a fixed reference level is known (Rahman et al., 2017), and environmental tracers have been used for understanding more complex connections (Harvey et al., 2019; Isokangas et al., 2017). Supported with information on topographic reliefs, routes of GW flows can also be inferred from discharge locations, such as springs and seepages (Autio et al., 2023), which often create unique habitats for threatened mire species (e.g., Åberg et al., 2019). The conditions of upstream peatlands impact the water quantity downstream, which can be measured from the water levels and in the river flows. For monitoring catchment quality downstream, the direct method is sampling water for laboratory analyses (Similä et al., 2014). Also, other field methods assessing the water colour, turbidity (e.g., Secchi disk) or appearing vegetation, algae or cyanobacteria development have been used. These aspects can be somewhat monitored with RS (see e.g., Schmugge et al., 2002), but this paper focuses on the indicators at the intervention site.

The recovery of peatland vegetation and its associated ecosystem services is typically the ultimate goal of restoration. Vegetation reestablishment is also crucial for the formation of a new permeable surface moss layer typically lost after drainage (Similä et al., 2014). Plant species composition (i.e., dominant plant species and their assemblage of species into communities) and structure (i.e., height and coverage) have generally been used as indicators of success (Haapalehto et al., 2017; Laine et al., 2011). A variety of graminoids, shrubs, forbs, *Sphagnum*, wet brown mosses, and trees can act as indicator species reflecting the overall change (González et al., 2013; Similä et al., 2014). Thorough surveys of species composition have been performed using permanent vegetation plots (Bonnett et al., 2009; Cris et al., 2014; D'Astous et al., 2013; Elo et al., 2024; Haapalehto et al., 2014, 2017). Peatland restoration also aims to recover the tree stand structure of the pristine state (Maanavilja et al., 2014; Similä et al., 2014). At forestry-drained sites with intensified tree growth, felling is applied to regain targeted level of openness (e.g., Hedberg et al., 2012), or sometimes to create tracks for forestry machinery (Similä et al., 2014). Commonly observed variables of tree-stand structure include species composition, size and age classes, trunk counts, canopy cover, basal area, height and trunk volume.

Drainage alters peat properties, often leading to the loss of natural microtopography, such as hummocks and hollows. One of the most relevant RS-compatible indicators is peat depth, which is conventionally measured through probing with steel rod or more accurately by observing the transition to mineral material from samples obtained by coring (Parry et al., 2014). Successful rewetting terminates peat mineralization and subsidence, induces swelling, and reactivates the accumulation of organic matter (Ikkala et al., 2022; Miller et al., 2008; Shantz and Price, 2006). Monitoring land surface elevation changes and peatland boundaries can help assess soil processes and carbon stocks (Carless et al., 2019; O'Leary et al., 2022; Richardson et al., 2010). Various methods have been used for these assessments, including poles fixed in the mineral soil below the peat (e.g., Hooijer et al., 2012), platens fixed at certain depths in the peat (Massop et al., 2024), levelling (Ryszard et al., 2020), and Real-Time Kinematic Global Navigation Satellite System (Ikkala et al., 2022; Regan et al., 2019). However, observing significant carbon accumulation with topographic data requires extended time series. Changes in CO_2 and CH_4 surface exchange rates have been measured on-ground at restored peatlands with portable chambers supplemented by eddy covariance (e.g., Lees et al., 2021b).

4. Remote sensing methods for monitoring recovering peatland processes

4.1. Hydrology

4.1.1. Soil surface moisture

The moisture at the soil surface, referring to the topmost 5 cm layer (Schmugge et al., 2002), can be quantitatively estimated with RS using either i) Synthetic Aperture Radar (SAR), ii) optical bands or spectral indices, or iii) thermal or optical trapezoid models (Table 3). Regardless of the chosen method, the measured signal requires calibration to account for land surface parameters before interpretation (Wang and Qu, 2009). Challenges typically occur when applying RS methods for before-after moisture comparisons with simultaneous land cover changes such as tree felling, excavation or vegetation development (Ball et al., 2023; Isoaho et al., 2024a). Furthermore, spectral and trapezoid methods have shown losing performance with increasing WT depths (>60 cm, Asmuß et al., 2019, or site-specifically at 0–100 cm, Burdun et al., 2023), supposedly due to the loss of capillary connections, i.e., the surface soil moisture does not depend on WT depth when it is great (Asmuß et al., 2019).

Active SAR method, which operates by transmitting and receiving microwave pulses, has been considered perhaps the most promising RS approach for soil surface moisture monitoring due to its i) direct sensitive to water, ii) ability to penetrate cloud cover and, to some extent, vegetation canopy, and iii) independence of solar radiation (Asmuß et al., 2019; Kornelsen and Coulibalya, 2013; Lees et al., 2021a; Stachowicz et al., 2024; Sterratt et al., 2024). However, SAR data interpretation requires accounting for surface roughness, seasonal vegetation dynamics, and open water bodies, as these factors influence backscatter signals and, consequently, soil surface moisture estimates (Bechtold et al., 2018). Digital Surface Models (DSMs) derived from Light Detection and Ranging (LiDAR) or photogrammetric Uncrewed Aerial System (UAS) Structure-from-Motion (SfM) data can explain the impacts of vegetation and surface roughness on the SAR data (Millard and Richardson, 2018). The above studies utilized the C-band SAR at a 5.7 cm wavelength, sub-wavelengths representing its approximate penetration depth in the soil. L-band SAR data with a longer 26.6 cm wavelength has been found to maintain high coherence even when travelling through tree cover and when open water is present (Kim et al., 2017). Some studies, on the other hand, have shown that C-band SAR data has sub-optimal performance when monitoring peatland WT depth (Isoaho et al., 2024b; Räsänen et al., 2022) and that ancillary data on the acquisition time and site are more important than backscatter information (Toca et al., 2023).

An alternative approach to estimating soil surface moisture distribution relies on the use of multispectral and hyperspectral optical imagery, which describe the spectral characteristics of the peat or vegetation cover, such as *Sphagnum* mosses (Harris and Bryant, 2009).

Specific moisture indices from handheld spectroradiometer studies such as Simple Ratio Water Index (Meingast et al., 2014) have encouraged further research with spatially continuous data. Spaceborne optical indices, such as Normalized Difference Moisture Index, Normalized Difference Water Index, and Short-wave Infrared (SWIR) Transformed Reflectance, or single bands, have been shown to work well and even better than C-band SAR data in monitoring peatland surface moisture or WT depth, particularly in boreal peatlands with few or no trees (Isoaho et al., 2024b; Kalacska et al., 2018; Lees et al., 2020; Jussila et al., 2024; Räsänen et al., 2022). Nevertheless, with coarser-resolution data, captured pixel values on peatlands typically consist of combined spectral reflections of several *Sphagnum* and vascular plant species, which might affect the index values (Pang et al., 2020). Similarly, the moisture variation of the *Sphagnum* inside single pixels, appearing more with

Table 3
Remote sensing methods suitable for monitoring **hydrology** in peatland restoration. Restored peatland sites are marked as **yellowed bold**, non-peatland sites as *greyed italic*.

Subject	Method	Source	Site type	Location	Source GSD
Soil surface moisture	C and L-band SAR	Kim et al. 2017	Forested swamp	USA	H
		Bechtold et al. 2018	Drained and natural peatlands	Germany	C
		Millard & Richardson 2018	Partly cultivated, forested and non-forested bog and fen	Canada	C
		Asmuß et al. 2019	Grassland fens	Germany	H
		Lees et al. 2021a	Blanket bog	UK	H
		Toca et al. 2023	**Forestry-drained and restored and** near-natural **peatlands**	UK	H
		Stachowicz et al. 2024	Various mire and peatland types, including bogs, fluviogenous and topogenous mires, and **drained and restored peatlands**	Poland	H
		Sterratt et al. 2024	**Forestry and peat removal drained restored lowland raised bog**	UK	H
	Spectral bands and indices	Harris & Bryant 2009	*Laboratory*, ombrotrophic bog	UK	VH, S
		Meingast et al. 2014	Poor fen	USA	S
		Banskota et al. 2017	Manipulated and natural peatland	USA	S
		Kalacska et al. 2018	Ombrotrophic bog	Canada	UH-H
		Lees et al. 2020	*Laboratory*, Near-natural and **restored blanket bogs**	UK	S
		Pang et al. 2020	*Sphagnum* peatland	China	H, S

		Kolari et al. 2022	Aapa mires, *laboratory*	Finland	UH, S
		Jussila et al. 2023	Relatively pristine open aapa mire fens	Finland	H
		Karlqvist et al. 2024	*Laboratory samples from undrained mires*	Finland	S
		Karlqvist et al. 2025	Undisturbed mires	Finland, Estonia	S
	Trapezoid Models	Wigmore et al. 2019	*Mountain valley floors including wetlands, meadows glazier and* peatbog.	Peru	UH
		Burdun et al. 2020a	Ombrotrophic bog	Estonia	H-VC
		Burdun et al. 2020b	Fens and ombrotrophic bogs	Estonia	H-VC
		Burdun et al. 2023	Various types and conditions including intact, drained and **restored peatlands**	Finland, Estonia, Sweden, Canada, USA	H
	TIR imaging	Luscombe et al. 2015	Blanket peatland	UK	VH
	Multi-method	Lendzioch et al. 2021	Montane raised ombrotrophic peat bog complex	Czech Republic	UH
		Räsänen et al. 2022	**Open and tree-covered, forestry-drained and restored and** pristine **peatlands**	Finland	H
		Isoaho et al. 2023	**Undrained but suffering from upslope forestry drainage and restored aapa mire fens**	Finland	UH
		Isoaho et al. 2024b	**Undrained but suffering from upslope forestry drainage and restored and** control **aapa mire fens**	Finland	H
Water flow routes	Flow accumulation and topographic wetness	Hasan et al. 2012	Mire peatland	Sweden	UH
		Carless et al. 2019	Blanket bog	UK	UH
		Ikkala et al. 2022	**Restored and** control **aapa mire fens**	Finland	UH

	GW discharge	Isokangas et al. 2019	Treatment peatland for mining area	Finland	UH
		Harvey et al. 2019	**Restored cranberry peatland**	USA	UH
		Watts et al. 2023	**Restored cranberry peatland**	USA	UH
Open water	Multispectral imaging	Cooley et al. 2017	*Marshland, spruce and birch forest, wetland*	Alaska	VH
		Jussila et al. 2023	Relatively pristine open aapa mire fens	Finland	H
	InSAR	Kim et al. 2017	Forested swamp	USA	H
	Multi-sensor	Krzepek et al. 2022	**Agriculture drained and rewetted peatland**	Germany	VH-H
	LiDAR	Andersen et al. 2017	*Tidal inlet system*	Denmark	UH
		Korpela et al. 2020	Raised bog	Finland	UH
		Rahman et al. 2017	Forested bog	Canada	UH

Ground sampling distance (GSD): UH = ultra-high ≤1 m, VH = very high ≤5 m, H = high ≤30 m, C = coarse ≤250 m, VC = very coarse >250 m, S = single points.

coarser spatial resolutions, has been shown to influence the RS observations (Harris and Bryant, 2009). Further advancements in soil moisture estimation could be achieved through continuous wavelet transformations for hyperspectral data rather than relying solely on indices derived from a few selected bands (Banskota et al., 2017; Karlqvist et al., 2024, 2025). Additionally, separate bands such as red (Isoaho et al., 2023, 2024b) and near-infrared (NIR, Kolari et al., 2022) reflectance have been shown to correlate with boreal peatland surface moisture.

Soil surface moisture can also be modelled by combining either SWIR or thermal infrared (TIR) data and an optical vegetation index (VI), using Optical Trapezoid Model or Thermal-Optical Trapezoid Model (TOTRAM), respectively (Burdun et al., 2020a). The spatial resolution typically poor for thermal sensors can be increased by attaching them to UAS (Isoaho et al., 2023). TOTRAM includes an assumption of moisture being the limiting factor for vegetation growth and evapotranspiration, but instead, they are typically restricted by temperature on boreal peatlands, which might limit the applicability of the model (Burdun et al., 2020a). The Optical Trapezoid Model has shown to perform better and the temporal correlation with soil surface moisture increases with higher spatial resolution despite spatial correlations were not found (Burdun et al., 2020b, 2020a, 2023). Besides TOTRAM, the spatial correlation between thermal emissivity and the soil surface moisture can be described using LiDAR-data-based Surface Roughness Index (Luscombe et al., 2015) to normalize the data of land surface structure effects. Other impacting factors such as local microclimates or GW discharge (see Section 4.1.2) might confuse the thermal methods as the natural thermal emissivity anomalies at such locations do not reflect the soil surface moisture. Besides temperature and spectral indices, also topomorphometric variables have shown importance in predicting soil surface moisture (Lendzioch et al., 2021).

4.1.2. *Water flow routes*

Data with sufficient spatial resolution such as UAS-SfM-based orthomosaic photographs can accurately document the locations and dimensions of restoration constructions. Orthomosaics can also help reveal surface flows of water and possible dam leakages, at least during the high-water season (Ikkala and Similä, 2024). The surface soil moisture assessment methods presented above can possibly identify the underground near-surface flow routes that are wetter than their surroundings. Wetness distributions and flow routes can also be simulated solely based on topography and soil information, with flow accumulation algorithms and Topographic Wetness Indices (Carless et al., 2019; Hasan et al., 2012; Ikkala et al., 2022). Deducing flow routes, however, requires a rather high (≤ metres) spatial resolution.

GW discharge locations can possibly be seen from aerial photography. However, temperature anomalies can act as a clearer tracer if the GW and surface temperatures differ enough (Ikkala and Similä, 2024; Watts et al., 2023). For instance, Isokangas et al. (2019) used UAS-based thermal imaging to point out the 4 °C GW discharge locations contrasting to the surface water temperature at 11 °C on a summer day. Harvey et al. (2019) used a similar approach to examine the discharged 12 °C GW to show up on top of the cooler −3 °C stream water on a winter day during stream and peatland restoration.

4.1.3. *Open water*

The open water distribution can be emphasized with spectral water and moisture indices which remove the effect of, e.g., soil and vegetation as demonstrated by Cooley et al. (2017) in a sub-arctic wetland. Spaceborne Interferometric SAR (InSAR) technology has been argued to be superior in mapping open water cover for large extents (Kim et al., 2017). However, other studies have shown that water surface areas in boreal fens can be monitored also with optical Sentinel-2 data (Jussila et al., 2024) or by fusing SAR and multispectral data (Krzepek et al., 2022).

Open water levelling is possible with LiDAR or UAS-SfM, particularly if there is opaque matter on or around the pond surface (Korpela et al., 2020). While water strongly absorbs NIR wavelengths commonly used in LiDAR, green wavelength LiDAR has shown potential for mapping water surface elevations, as Andersen et al. (2017) showed in a tidal inlet system. UAS-SfM can also determine the water surface levels near the water edge where land pixels can act as common features for accurately building the DSM (Kohv et al., 2017). Rahman et al. (2017) showed the interpolation of SfM-levelled ponds on a flat site to interpolate the WT level in the soils in between when enough ponds exist.

4.2. Vegetation

4.2.1. Ground and field layer

RS can be used for mapping and classifying the spatial patterns and changes due to peatland restoration (Table 4) of, e.g., i) land cover or vegetation types (Ball et al., 2023; Beyer et al., 2019; Frick et al., 2011; Koch et al., 2017; Middleton et al., 2012; Millard et al., 2020; O'Leary et al., 2023; Räsänen and Virtanen, 2019; Sirin et al., 2020; Steenvoorden et al., 2022, 2023, 2024; White et al., 2020), ii) peatland habitat condition (Artz et al., 2019; Ball et al., 2023; Steenvoorden et al., 2024), iii) floristically defined plant communities and assemblages (Harris et al., 2015; Isoaho et al., 2024a; Räsänen et al., 2020a; Wolff et al., 2023), iv) single plant species or plant functional types (such as *Sphagnum* mosses or graminoids, or plant strategy types; Cole et al., 2014a; Cole et al., 2014b; Harris and Bryant, 2009; Kattenborn et al., 2017; Räsänen et al., 2020a; Räsänen et al., 2025; Simpson et al., 2024; Steenvoorden et al., 2023; Wolff et al., 2024), and v) plant functional traits (such as vegetation height, Leaf-Area Index, nutrient content) (Kalacska et al., 2015; Kattenborn et al., 2017). Besides soil surface moisture, spectral methods such as broad or narrow-band indices can also potentially be used to examine the changes in stress of plants and primary production of peatland vegetation (D'Acunha et al., 2018; Lees et al., 2020; McPartland et al., 2018; Rastogi et al., 2019) or changes vegetation phenology (Cole et al., 2014b) and albedo (Burdun et al., 2025; Worrall et al., 2022, 2025). However, VIs also become affected by many other environmental factors such as temperature, vegetation composition and disturbances such as drainage and rewetting (McPartland et al., 2018). Consequently, VI changes in restoration of forestry-drained peatlands might appear bidirectional, since the drained-state species often deteriorate after rewetting, before the hydrophilic vegetation takes hold.

There have been little RS studies on analyzing detailed changes in plant community structure after peatland restoration, probably due to the lack of detailed plant species monitoring data in restored sites and overall difficulty in detecting fine-tuned changes in vegetation. To our knowledge, the only studies analyzing post-restoration vegetation changes with RS are Isoaho et al. (2024a) and Räsänen et al. (2025). Other RS studies have examined, for example, whether the spectral properties of restored peatlands resemble spectral properties of undrained peatlands and how the difference in signatures between restored and undrained sites reduces after time since restoration (Ball et al., 2023), and how optical RS can be used to analyze long-term peatland vegetation type change in undrained peatlands (Granlund et al., 2021; Kolari et al., 2022; Steenvoorden et al., 2022). Restored, degraded and natural peatlands also have shown to reflect different SAR signatures (Ball et al., 2023; White et al., 2020).

In general, the more abundant a specific vegetation property is and the more distinct spectral and structural properties it has, the easier it is to detect it with RS (Räsänen et al., 2020a). As peatland vegetation is typically characterized by fine-scale spatial heterogeneity controlled by microtopography, soil pH and nutrient content, very high to ultra-high spatial resolution (from centimetres to a few meters) has generally been recommended (Räsänen and Virtanen, 2019; Steenvoorden et al., 2023). However, some changes can also be observed with coarser spatial resolution; for instance, long-term changes in spectral properties such as a general trend in the increase of *Sphagnum* cover (D'Acunha et al., 2018; Kolari et al., 2022), change in peatland spectral properties after restoration (Ball et al., 2023; Räsänen et al., 2025), or changes along floristic gradients (Isoaho et al., 2024b). Moreover, some changes can be observed with coarse spectral resolution data: for instance, Kalacska et al. (2013) mapped *Eriophorum vaginatum* coverage with simple Red-Green-Blue (RGB) UAS imagery while Knoth et al. (2013) physically modified a conventional RGB camera to record also NIR wavelengths. Kolari et al. (2022) and Granlund et al. (2021) analyzed fen-bog transitions with historical black and white aerial imagery and contemporary drone or aerial imagery. Nevertheless, detection of more fine-tuned changes in the plant community composition may require finer spectral resolution, even hyperspectral sensors (McPartland et al., 2019; Pang et al., 2022; Salko et al., 2023; Wolff et al., 2024). Finally, it has also been shown that multi-sensor RS (i.e., combination of structural and spectral data) has a higher prediction accuracy than using only one sensor in mapping peatland vegetation (Beyer et al., 2019; Räsänen and Virtanen, 2019; Schulte to Bühne and Pettorelli, 2018; Wang et al., 2023).

4.2.2. Trees

RS from optical sensors has typically been employed for detecting the tree-covered areas on peatlands (e.g., Ball et al., 2023; Knoth et al., 2013; Langanke et al., 2007; McPartland et al., 2019). Integration with other sensors, particularly airborne LiDAR, increases the classification accuracy like Millard et al. (2020) showed for recognizing fens, open shrub bogs, and treed bogs. When using hyperspectral images, the minimum resolution providing sufficient detail for separating treed fens from open ones is 1 m (McPartland et al., 2019). Lower-spatial-resolution satellite data also remains useful for restoration monitoring, given that the structural change is significant, such as a clear cut aiming at an open habitat in the restoration of a densely forested peatland. For instance, Bourgeau-Chavez et al. (2015, 2017) utilized optical and SAR satellite imagery (10–30 m) to distinguish treed bogs and fens from open and shrubby sites. Also, Frick et al. (2011) presented how spaceborne panchromatic images (0.5 m) can support lower-spatial-resolution (down to 20 m) multispectral images, when differentiating woods and shrubs from other vegetation covers in rewetted fens.

The slow process of the tree stand succession necessitates a prolonged observation period (Bożek et al., 2019). Hence, the long-term recovery success of the openness is often predicted from the post-restoration seedlings (Similä et al., 2014). Early identification of seedling distribution is possible using UAS imagery (Feduck et al., 2018). Conversely, without tree felling, rewetting of tree-covered peatlands typically leads to increased tree mortality due to root zone saturation (Maanavilja et al., 2014). Tree deterioration and mortality can be monitored by identifying the changes in spectral and structural traits (Lausch et al., 2017), using optical sensors onboard uncrewed (Thiel et al., 2020) or crewed aircraft (Pasher and King, 2009) or satellites (Garrity et al., 2013) besides airborne LiDAR approaches (Yao et al., 2012).

Parameters describing the tree-stand structure can be retrieved from various sources such as UAS-SfM photogrammetry (Goodbody et al., 2019; Iglhaut et al., 2019; Noordermeer et al., 2019), airborne LiDAR (Lutz et al., 2008; Niemi et al., 2015; White et al., 2016), aerial images (Bożek et al., 2019), spaceborne LiDAR (Neuenschwander and Magruder, 2019), X-band InSAR (Karila et al., 2015; Solberg et al., 2014), or through the integration of multiple sensors (Bergen et al., 2009; Hyde et al., 2006; Karila et al., 2015; Peuhkurinen et al., 2018).

Only some of these methods have been tested in forested peatlands (Table 4). For instance, Niemi et al. (2015) found airborne LiDAR suitable for predicting forest inventory attributes in slow-growth forestry-drained peatlands when supported by field data. Likewise, Solberg et al. (2014) estimated tree heights with InSAR and LiDAR in a study area including forested peatlands. Currently, airborne LiDAR is perhaps the most effective RS data source for comprehensive mapping of tree-stand structure due to its ability to penetrate the canopy, thereby powerfully surveying and classifying also the sub-canopy, understorey and ground (Lutz et al., 2008; Noordermeer et al., 2019; White et al., 2016). UAS-SfM can achieve comparable accuracy (Iglhaut et al., 2019), but it is limited to measuring changes in tree height and canopy cover as structures below the top envelope remain shaded (Goodbody et al., 2019; Noordermeer et al., 2019).

Table 4
Remote sensing methods suitable for monitoring **vegetation** in peatland restoration. Restored peatland sites are marked as **yellowed bold**, non-peatland sites as *greyed italic*.

Subject	Method	Source	Site type	Location	Source GSD
Ground and field layer vegetation structure	RGB classification	Kalacska et al. 2013	Ombrotrophic bog	Canada	UH
		Koch et al. 2017	Coastal paludification fen	Germany	UH
		Steenvorden et al. 2022	**Partly restored, disturbed raised bogs, mountain blanket bogs and western type blanket bogs**	Ireland	UH
		Steenvorden et al. 2023	Intact and cut raised bogs	Ireland	UH
		Steenvorden et al. 2024	**Mostly degraded due to drainage and restored raised bogs**	Ireland	UH
	Multispectral methods	Knoth et al. 2013	**Rewetted cutover bog**	Germany	UH
		D'Acunha et al. 2018	**Rewetted bog**	Canada	C
		McPartland et al. 2018	Ombrotrophic bogs and rich riverine fens including treatments	USA, Alaska	S
		Rastogi et al. 2019	Poor fen	Poland	S
		Lees et al. 2020	*Laboratory*, Near-natural and **restored blanket bogs**	UK	S
		Sirin et al. 2020	**Rewetted peatlands**	Russia	H-C
		Worrall et al. 2022	**Rewetted horticulture exploited raised bogs**	UK	VC
		Isoaho et al. 2024a	**Restored spruce mire forests, pine mire forests and open mires and** their pristine and drained references	Finland	H-C
		Keränen et al. 2024	**Mostly open undrained but suffering from upslope forestry drainage and restored**	Finland	UH-H

			aapa mire fens		
		Simpson et al. 2024	Drained and naturally rewetted blanket bog with sheep grazing	UK	UH
		Räsänen et al. 2025	Restored spruce mire forests, pine mire forests and open mires and their pristine and drained references	Finland	H
		Burdun et al. 2025	Restored forestry and agriculture-drained, cutover and other peatlands and their pristine references	Finland, Estonia, Latvia, Lithuania, UK, Canada, USA	VC
		Worrall et al. 2025	Restored cutover, grazed and wildfire degraded and near-natural blanket bogs and	UK	VC
	Hyperspectral methods	Middleton et al. 2012	Aapa mire fen	Finland	VH
		Cole et al. 2014a	Upland blanket peatland under restoration	UK	UH
		Cole et al. 2014b	Upland blanket peatland under restoration	UK	S
		Harris et al. 2015	Ombrotrophic bog	UK	UH
		Kalacska et al. 2015	Ombrotrophic bog	Canada	UH, S
		Kattenborn et al. 2017	Rich riverine fens, poor calcareous fens, raised bog	Germany	VH-H
		McPartland et al. 2019	Ombrotrophic bogs and rich riverine fens including treatments	USA, Alaska	UH, S
		Pang et al. 2022	Pristine fens	Finland	S
		Salko et al. 2023	*Laboratory*	Finland	S
		Wolff et al. 2024	Aapa mire complexes with fen and bog features and micropatterns	Finland	UH, S
	Multi-sensor methods	Harris & Bryant 2009	*Laboratory*, ombrotrophic bog	UK	VH, S

		Frick et al. 2011	**Rewetted polder grassland peatlands**	Germany	UH-H
		Artz et al. 2019	All peatlands in Scotland	UK	VH-VC
		Beyer et al. 2019	**Rewetted coastal flood mire fen**	Germany	UH
		Räsänen & Virtanen 2019	Riparian fen and pine bog	Finland	UH-VH
		Räsänen et al. 2020a	Treeless fens	Finland	UH-VH
		White et al. 2020	**Rewetted cutover peatland**	Canada	UH-H
		Kolari et al. 2022	Aapa mires, laboratory	Finland	UH, S
		Ball et al. 2023	**Forestry-used and restored semi-natural blanket bog**	UK	UH-C
		O'Leary et al. 2023	**Former raised bog with cutover use targeted for restoration**	Ireland	H-C
		Wang et al. 2023	Inland river delta including perched wetland basins	Canada	UH-H
		Wolff et al. 2023	Aapa mire complexes with patterns of fen and bog parts	Finland	UH
	InSAR	Millard et al. 2020	Open fen, open shrub bog, treed bog, cutover, agricultural field and *upland forest*	Canada	H
Tree stand structure	RGB imaging	Langanke et al. 2007	**Drained and restored sub-alpine raised bog**	Austria	UH
		Bożek et al. 2019	*Treated forest*	Poland	H
	Multispectral methods	Pasher & King 2009	*Sugar-maple-dominated forest*	Canada	UH
		Frick et al. 2011	**Rewetted polder grassland peatland**	Germany	UH-VH
		Garrity et al. 2013	*Pine and juniper-dominated forest*	USA	UH-VH

		Knoth et al. 2013	**Rewetted cutover bog**	Germany	UH
		Feduck et al. 2018	*Treated forest*	Canada	UH
		Ball et al. 2023	**Forestry-used and restored semi-natural blanket bog**	UK	UH-C
	Hyperspectral methods	McPartland et al. 2019	Ombrotrophic bogs and rich riverine fens including treatments	USA, Alaska	UH, S
	LiDAR	Yao et al. 2012	*Mountain forests*	Germany	UH
		Niemi et al. 2015	Forestry-drained peatlands	Finland	VH
	Spaceborne LiDAR	Neuenschwander & Magruder 2019	Forest, savanna/woodland	Canada, Botswana, Brazil, Finland	VC
	SAR and InSAR	Bourgeau-Chavez et al. 2015	Coastal wetlands, fens and bogs	USA, Canada	H
		Bourgeau-Chavez et al. 2017	Wooded bog, open fen, shrubby fen, treed fen	USA, Canada	H
		Solberg et al. 2014	*Coniferous forest* with intermixed peatlands	Norway	UH-H
		Karila et al. 2015	*Pine and spruce-dominated treated forest*	Finland	VH
	Multi-sensor methods	Hyde et al. 2006	*White fir, red fir, ponderosa pine, giant sequoia, and montane hardwood conifer forest*	USA	VH-H
		Peuhkurinen et al. 2018	*Pine and spruce dominated forest*	Russia	UH-H
		Noordermeer et al. 2019	*Pine and spruce dominated forest*	Norway	UH-VH
		Millard et al. 2020	Open fen, open shrub bog, treed bog, cutover, agricultural field and *upland forest*	Canada	H
		Thiel et al. 2020	*Untreated, beech-dominated forest*	Germany	UH

GSD: UH = ultra-high ≤1 m, VH = very high ≤5 m, H = high ≤30 m, C = coarse ≤250 m, VC = very coarse >250 m, S = single points.

4.3. Peatland elevation and structure

4.3.1. Topography and microtopography

The two main high precision RS approaches for mapping topography and microtopography (Table 5), i.e., the large-scale and sub-metre variation in elevation, are LiDAR (Carless et al., 2019; Hasan et al., 2012; Kincey and Challis, 2010; Korpela et al., 2009) and UAS-SfM (Harris and Baird, 2019; Ikkala et al., 2022; Mercer and Westbrook, 2016; Scholefield et al., 2019). Also, spaceborne InSAR has been shown as an option to estimate elevation changes including short-term surface oscillation (mire breathing) that should be considered when topographical changes are measured (Alshammari et al., 2020; Ghezelayagh et al., 2024; Ghezelayagh et al., 2025; Tampuu et al., 2020). LiDAR technology is known for its superior capability to produce Digital Terrain Models (DTMs) also through canopy while SfM leaves voids in the surface below dense vegetation (Lovitt et al., 2017). However, LiDAR-derived DTMs might also distort due to the covering vegetation (Korpela et al., 2009). Even so, both UAS-SfM and LiDAR technologies can predict peatland microforms efficiently at a vertical accuracy of $<$0.1 m (Korpela et al., 2009, 2020; Mercer and Westbrook, 2016). Even if the peatland surface is inundated, green laser LiDAR can map the bathymetry of clear shallow waters as Andersen et al. (2017) showed in a tidal inlet system.

Variance and semivariance functions can be derived from DTM data to improve microform classification performance compared to spectral data only (Anderson et al., 2010). Indicators such as Lagg Width Index, Lateral Slope Index and Peatland Topographic Index have also been developed to describe the topographic properties of the site (Richardson et al., 2010). Specifically, Harris and Baird (2019) applied a multivariable method in topographic and morphometric classification of UAS-derived DSM. In addition, erosion and concurrent accumulation of fine-particles (Kincey and Challis, 2010; Scholefield et al., 2019) and crack formation related to shrinkage of drying peat, potential for producing unintended flow routes (Holden et al., 2006) can be tracked with both UAS orthomosaics and DTMs.

Besides monitoring the subsidence, swelling and carbon accumulation processes of peatlands, and recovery of natural microforms, elevation surveys can help control the aimed disappearance of anthropogenic drainage (ditches and canals) and restoration features (e.g., spoil piles, machinery pathways, or roads), and in specific, the subsidence and performance of the restoration constructions made of peat such as dams and embankments (FAO, 2020).

4.3.2. Peat structure and properties

Geophysical instruments such as Ground-Penetrating Radar (GPR) have been used on ground for monitoring peatland structure (Isokangas et al., 2017; Kettridge et al., 2008). Recent attempts to attach GPR to UAS have been reported but flying altitude must be as low as 50 cm to penetrate the air-ground boundary (e.g., Henrion et al., 2025). Together with ground sampling, such GPR systems might have the potential to quantify the thickness ($>$ 10 cm) of fresh *Sphagnum* peat at the restored sites where the drained, well-decomposed and compacted peat layer forms a distinct boundary against the freshly accumulating biomass above (Kettridge et al., 2008; Sass et al., 2010).

Gamma-ray spectrometers, on the other hand, have been used from manned airborne platforms to delineate peat deposits with depths of $<$50 cm (Minasny et al., 2019), but the gamma-ray data can also predict peat depths when used together with high-spatial-resolution DTMs (Gatis et al., 2019). Gamma-ray sensors are light enough to be attached even to medium-sized UAS (Woodbridge et al., 2023). A lower flight altitude typically narrows the signal footprint compared with a crewed aircraft (Martin et al., 2016; O'Leary et al., 2022). Deeper peat layers ($>$ 1 m) have been surveyed from crewed aircraft (Minasny et al., 2019; Silvestri et al., 2019), and recently, with UAS using electromagnetic induction (Karaoulis et al., 2022). Gamma-ray and electromagnetic surveys can be combined to cover the entire typical peat depth range (Beucher et al., 2020). UAS-based geophysical methods typically require very low ($<$ 5 m) flight altitudes, which necessitates equipping the UAS with active radars for real-time terrain or surface-following capabilities.

On spaceborne platforms, peat properties such as bulk density and nitrogen and carbon contents have been shown to correlate spatially with L-band SAR backscatter (Takada et al., 2009). Furthermore, hyperspectral sensors can record the detailed spectral characteristics of peat, and hence, provide information on its origin (*Sphagnum* versus *Carex*) and properties (McMorrow et al., 2004), at least in the areas where the peat surface is not obscured by vegetation. In addition, Aitkenhead and Coull (2020) found correlations between soil attributes (bottom of the organic layer, carbon proportion and soil bulk density) and neural networks using Landsat 8 data and airborne geospatial datasets.

4.4. Greenhouse gas emissions

4.4.1. Carbon dioxide exchange

The determination of CO_2 balance over peatlands using RS (Table 6) is based on either i) land cover classification (e.g., Heiskanen et al., 2021) or ii) estimating the fluxes through Gross Primary Production derived from Photosynthetically Active Radiation, using, e.g., Light Use Efficiency models, and ecosystem respiration models (e.g., Lees et al., 2019; Burdun et al., 2021; Dąbrowska-Zielińska et al., 2022; Junttila et al., 2021; Kross et al., 2013; Zhou et al., 2023). Classification methods expand the ground-measured sequestration rates to larger extents using the RS-determined areas of carbon-similarity classes. However, the availability of carbon flux data from varying environments is limited (Crichton et al., 2015). In turn, Light Use Efficiency models can consider the sequestration heterogeneity utilizing correlation between the Gross Primary Productivity (GPP) and the vegetation reflectance in the RGB, Rededge and NIR wavelengths (Lees et al., 2018).

Light Use Efficiency models typically make use of a VI as a proxy of photosynthesis (Lees et al., 2018). However, broadband VIs such as Normalized Difference VI measuring the vegetation greenness might not necessarily reflect the photosynthesis rate, and the correlation is strongly season-dependent due to the developing phenology (Balzarolo et al., 2016; Lees et al., 2020; Purre et al., 2019) or the physiological changes in case of evergreen vegetation (Zarco-Tejada et al., 2013). Photochemical Reflectance Index, Chlorophyll Index and Chlorophyll Fluorescence are preferable, but they require an advanced spectral resolution (Kross et al., 2013; Lees et al., 2020; Zarco-Tejada et al., 2013). The broadband VIs can provide more accurate GPP estimates when combined with thermal data into a Temperature and Greenness model that can better explain the impact of daily weather variation on GPP (Lees et al., 2021b).

Assessing the Net Ecosystem Exchange requires data also on ecosystem respiration, which usually relies on the known relationships with soil surface moisture (WT depth) and temperature (Anderson et al., 2008), or relationships with net ecosystem production or GPP (e.g., Vourlitis et al., 2003). Also, green area of vascular plant vegetation is well correlated with gross photosynthesis, enabling the use of spatial parameters such as Green Chromatic Coordinate, Leaf-Area Index and Vascular Green Area to obtain proxies of CO_2 exchange (Juutinen et al., 2017; Peichl et al., 2015; Räsänen et al., 2020b). Carbon flux research has conventionally focused on satellite platforms (Lees et al., 2018) despite spatial heterogeneity being the main challenge (Kalacska et al., 2018). Essentially, the level of detail of carbon exchange assessment with RS is defined by the mapping scales of WT and vegetation cover (Räsänen et al., 2021). Detailed photosynthesis and Net Ecosystem Exchange modelling with airborne hyperspectral data have shown improved correlations according to higher spatial, spectral and radiometric resolutions (Arroyo-Mora et al., 2018; Kalacska et al., 2018; Zarco-Tejada et al., 2013).

4.4.2. Methane exchange

RS of CH_4 emissions is a less-studied topic and requires different tools and methods compared with CO_2 (Lees et al., 2018). One of the rare examples of the integrated CO_2 and CH_4 flux approaches is the biophysical Terrestrial Carbon Flux Model (Watts et al., 2014). Typically, RS products are used to support the modelling of the on-site CH_4 measurements from chambers or eddy covariance (Ingle et al., 2023). As methanogenesis is related to high WT level, soil moisture indices such as Normalized Difference Water Index and Tasseled Cap Transformation Wetness Index have shown success in extrapolation (Sturtevant and Oechel, 2013; Tagesson et al., 2013). WT depth is also a spatial correlative of microtopography and thus, mapping the surface elevations in ultra-high spatial resolution can support the modelling (Lovitt et al., 2018). To supplement the moisture data, vegetation indices such as Normalized Difference VI and Normalized Difference Red Edge Index have been used to consider the impacts of land cover (Sturtevant and

Table 5
Remote sensing methods suitable for monitoring **peatland elevation and structure** in peatland restoration. Restored peatland sites are marked as **yellowed bold**, non-peatland sites as *greyed italic*.

Subject	Method	Source	Site type	Location	Source GSD
Topography and microtopography	UAS DSM	Harris & Baird 2019	**Self-restoring blanket peatland**	UK	UH
		Mercer & Westbrook 2016	Alpine open peatland	Canada	UH
		Scholefield et al. 2019	Blanket bog	UK	UH
		Ikkala et al. 2022	**Restored and** control **aapa mire fens**	Finland	UH
	LiDAR	Korpela et al. 2009	Eccentric raised bog	Finland	UH
		Kincey & Challis 2010	*Upland moor*, raised bog	UK	UH
		Richardson et al. 2010	*Forested wetland* (partly peatland)	Canada	VH
		Hasan et al. 2012	Mire peatland	Sweden	UH
		Andersen et al. 2017	*Tidal inlet system*	Denmark	UH
		Carless et al. 2019	Blanket bog	UK	UH
	InSAR	Alshammari et al. 2020	Diverse blanket bogs	UK	C
		Tampuu et al. 2020	Open raised bog	Estonia	VH-H
		Ghezelayagh et al. 2024	River valley with peatlands impacted by agricultural drainage	Poland	C
		Ghezelayagh et al. 2025	River valley with peatlands non-drained and impacted by agricultural drainage	Poland	C
	Multi-sensor	Anderson et al. 2010	Ombrotrophic lowland raised bog	UK	UH
		Lovitt et al. 2017	Open, shrubby and treed bog	Canada	UH
		Korpela et al. 2020	Raised bog	Finland	UH

Peat structure and properties	UAS GPR	Henrion et al. 2025	**Forestry-drained and restored peatland**	Belgium	VH
	Airborne electromagnetics	Silvestri et al. 2019	Small bogs	Norway	H
		Beucher et al. 2020	Agricultural riparian fen peatland	Denmark	H
		Karaoulis et al. 2022	*Polder, riverside, man-made environment*	Netherlands	H
	Airborne gamma-ray	Martin et al. 2016	*Urban and rural areas*	Japan	UH
		Gatis et al. 2019	Blanket bog	UK	H
		Woodbridge et al. 2023	*Uranium mine*	UK	H
		O'Leary et al. 2022	Peatlands	Ireland	C
	SAR	Takada et al. 2009	Drained *Sphagnum* mire	Japan	H
	Hyperspectral imaging	McMorrow et al. 2004	Blanket peatland	UK	VH
	Multi-sensor	Aitkenhead & Coull 2019	Peat soils of Scotland including **restoration sites**	UK	C

GSD: UH = ultra-high ≤1 m, VH = very high ≤5 m, H = high ≤30 m, C = coarse ≤250 m, VC = very coarse >250 m, S = single points.

Oechel, 2013). As multi-sensor approaches improve the land cover classification (e.g., Schulte to Bühne and Pettorelli, 2018; Wang et al., 2023), compiling, e.g., optical, LiDAR and SAR data also increase the prediction accuracy of CH_4 exchange (Räsänen et al., 2021).

4.4.3. Uncrewed greenhouse gas probing

Surface-atmosphere fluxes can also be inferred using sampling systems such as UAS-based concentration sensors. For instance, Kunz et al. (2020) implemented a UAS experiment outside peatlands to estimate CO_2 respiration that takes advantage of stable nighttime conditions and concluded the measured fluxes to be plausible, but the method is applicable only for ecosystems larger than 10 km while many peatlands tend to be smaller. For CH_4, Lampert et al. (2020) recorded 1-km-high vertical profiles of different isotopes to track the gas origin inside an atmospheric boundary layer over a rewetted peatland. On Arctic ecosystems, a moving UAS probe has been directly connected to a gas analyzer (Scheller et al., 2022).

5. Implementing remote sensing monitoring in peatland restoration

5.1. Platforms and their selection

Each remote sensing platform has its specific strengths and weaknesses in terms of peatland restoration monitoring. Readily available spaceborne data typically provides i) large coverage for evaluation of restoration impacts at regional, national and global levels, ii) long time series (e.g., Landsat and SPOT) required for monitoring slow vegetative succession of several decades after rewetting and iii) high temporal resolution that is unrivalled by conventional airborne missions (Reif and Theel, 2016). However, autonomous self-recharging UASs might provide unseen temporal resolutions for airborne missions in the future (Zhao et al., 2024). Peatland restoration sites are often in remote areas. The smallest UASs are lightweight and easily transportable even by walking, but larger and more stable uncrewed or crewed aircraft are needed for carrying heavy and sensitive sensors. The larger uncrewed aircraft typically requires launching near the car which might be an issue for the sites far away from the road network due to the visual line of sight requirements of UAS operation.

The spatial resolution of data produced is primarily defined by the platform (Fig. 2). It should be selected based on the minimum level of accuracy needed considering the scale of the site and the restoration indicators under interest. The typical scale of microtopography, in connection with soil surface moisture conditions, vegetation succession and carbon balance, varies from <1 m (Becker et al., 2008; Carless et al., 2019; Korpela et al., 2020) to 10 m or, for elongated structures, even 100 m (Keränen et al., 2024) on boreal peatlands. Generally, the maximum pixel size should be one-third of the features under inspection (Nagendra, 2001). UAS can distinguish details such as recovered wet flarks or individual seedlings, but only over a limited area. Besides, ultra-high spatial resolution of UAS data interferes with specific issues such as captured disruptive details, e.g., shadows (Pasher and King, 2009; Reif and Theel, 2016), and canopy movement of tall vegetation due to wind (Mercer and Westbrook, 2016). Furthermore, higher spatial and temporal resolutions always correspond to higher requirements for data storage and processing capacities.

Each RS platform and method involves associated costs (e.g., data or sensor costs and required field work for acquisition and model calibration and validation) which need to be considered (Klemas, 2013). Any attempts to compare the costs are complex due to the varying nature of data provided by third parties (commercially or free of charge), and data requiring personal device purchases (with rapidly developing pricing and varying operation degrees). With optical satellite sensors, cloud cover often hides the land surface (Wang and Qu, 2009), while also airborne missions are influenced by weather conditions (Watts et al., 2023).

5.2. Multi-sensors approaches

The large variation in RS specification and limitations of each method highlights the importance of multi-sensor and multi-platform approaches for capturing different restoration indicators. This is attributed to the variation in sensitivity of different sensors and their accuracy. For instance, while SAR sensors exploit the sensitivity of

Table 6
Remote sensing methods suitable for monitoring **greenhouse gas emissions** in peatland restoration. Restored peatland sites are marked as **yellowed bold**, non-peatland sites as *greyed italic*.

Subject	Method	Source	Site type	Location	Source GSD
CO_2 Exchange	RGB imaging	Becker et al. 2008	Oligotrophic low-sedge pine fen	Finland	UH
		Peichl et al. 2015	Oligotrophic, minerogenic, mixed mire system	Sweden	UH
	Multispectral imaging	Vourlitis et al. 2003	*Tundra river basin*	Alaska	VC
		Kross et al. 2013	Treed and non-treed fens	Canada, Finland	VC
		Crichton et al. 2015	Ombrotrophic lowland raised bog	UK	H
		Balzarolo et al. 2016	*Croplands, forests, grasslands, open shrublands, woody savanna*	Brazil, Canada, Germany, Finland, French Guiana, Japan, Netherlands, USA	VC
		Juutinen et al. 2017	*Coastal tundra including* dry fens, wet fens and bogs	Russia	UH-VH
		Lees et al. 2019	**Bogs restored after forestry drainage peat extraction and near-natural bogs**	Ireland, UK	C
		Purre et al. 2019	**Restored milled bogs**	Estonia	UH
		Junttila et al. 2021	Fens and a bog	Sweden, Finland	H-VC
		Zhou et al. 2023	**Grassland-drained and restored peatland**	Germany	H-VC
	Hyperspectral imaging	Zarco-Tejada et al. 2013	*Olive orchard farm*	Spain	UH
		Arroyo-Mora et al. 2018	Ombrotrophic bog	Canada	UH
		Kalacska et al. 2018	Ombrotrophic bog	Canada	UH-H

	Multi-sensor methods	Anderson et al. 2008	*Grass-dominated agricultural field*	USA	H-VC
		Lees et al. 2020	*Laboratory*, Near-natural and **restored blanket bogs**	UK	S
		Räsänen et al. 2020b	Oligotrophic to eutrophic fen	Finland	UH-VH
		Burdun et al. 2021	Intact, abandoned partly drained cutover and **self-restoring peatlands**	Estonia	H-VC
		Lees et al. 2021b	**Forestry-drained and restored blanket bog**	UK	C, S
		Dąbrowska-Zielińska et al. 2022	Agriculture drained lowland valley mire	Poland	H-VC
	UAS probing	Kunz et al. 2020	*Pasture, crops, coniferous and mixed forests*	Germany	S
CH_4 Exchange	Multispectral methods	Sturtevant & Oechel 2013	*Wet meadow tundra*	Alaska	VH-H
		Tagesson et al. 2013	*Wet tundra with high, dry heath areas and* low, wet fens	Greenland	H-VC
	Multi-sensor methods	Watts et al. 2014	Peatlands *and tundra*	Finland, Sweden, Russia, Greenland, Alaska	C-VC
		Ingle et al. 2023	Raised bog	Ireland	VH
		Räsänen et al. 2021	*Coniferous-dominated and mixed forests, mountain tundra,* partly drained open peatlands	Finland	UH-H
	UAS DSM	Lovitt et al. 2018	Treed and open bog	Canada	UH
	UAS probing	Lampert et al. 2020	**Rewetted polder peatland**	Germany	S
		Scheller et al. 2022	Arctic permafrost fen	Greenland	S

GSD: UH = ultra-high ≤1 m, VH = very high ≤5 m, H = high ≤30 m, C = coarse ≤250 m, VC = very coarse >250 m, S = single points.

microwave spectrum to soil surface moisture, spectral data can be used to track vegetation reflectance and phenology. Also, the detailed 3D structural models describing both vegetation structure and topography derived with SfM or LiDAR can supplement these datasets, e.g., by minimizing the surface interference in soil moisture predictions from SAR data (Millard and Richardson, 2018).

Similarly, for detecting vegetation changes, it is important to integrate spectral with topography information (e.g., Räsänen and Virtanen, 2019; Wolff et al., 2023). Nevertheless, further boosts in prediction accuracy can possibly be achieved by including also active microwave data or multiple different types of passive data (multispectral, hyperspectral, thermal) (e.g., Ball et al., 2023; McPartland et al., 2019; Wang et al., 2023). Similarly, GHG flux monitoring benefits from multi-sensor approaches. In this context, it is essential to obtain proxy information for spatial patterns of wetness, vegetation, and temperature which are the major controls of GHG uptake and emissions (Dąbrowska-Zielińska et al., 2022; Heiskanen et al., 2021; Junttila et al., 2021). Furthermore, airborne and UAS-based data play a crucial role in calibrating or upscaling coarser-resolution spaceborne datasets, ensuring improved spatial accuracy in peatland restoration assessments (Klemas, 2013; Keränen et al., 2024).

5.3. When should remote sensing campaigns for peatland restoration be performed?

Monitoring timescale should be chosen according to the rate of the changes under observation as rewetting might be nearly instant (Laine et al., 2011) while vegetational succession takes several years or up to decades for communities and centuries for tree stand structures (Haapalehto et al., 2011). We suggest that RS enables monitoring the changes of the post-restoration development within a similar timeframe as has been covered by ground measurements concerning hydrological recovery (at least the first 0–6 years, Laine et al., 2011; Menberu et al., 2016; Tolvanen et al., 2020) and ecological succession (2–10 years, Haapalehto et al., 2011, 2017; Laine et al., 2011, 2019; Maanavilja et al., 2014) in boreal forestry-drained peatlands. Even shorter-term schemes are relevant to show instant results, e.g., of dam leakage needed for quick corrective actions, or tree mortality due to raised WT, both being expected soon after rewetting (Similä et al., 2014).

Monitoring typically requires multi-year time series to account for the variation in weather conditions within and between years (Purre et al., 2019). Furthermore, boreal peatland vegetation has notable spectral and structural variation driven by changes in season and related ecological conditions (Cole et al., 2014b; Millard et al., 2020). Optimally, RS datasets should be acquired multiple times during a growing season for successfully predicting the change of the restoration indicators (Isoaho et al., 2024b; Millard et al., 2020; Räsänen et al., 2025). The most success in classifying vegetation using spectral data might be expected in the beginning or middle of the growing season for boreal peatlands (Cole et al., 2014b; Isoaho et al., 2024b; Räsänen et al., 2025). However, if a certain species is chosen as an indicator of restoration success, the acquisition should be conducted at the time of maximum leaf area, which may be difficult to achieve under the constraints of weather. Low-altitude high-spatial-resolution optical data suffers particularly from the anisotropic properties of vegetation that are lowest in springtime but can also be managed with calibration of illumination and acquisition geometries (Kalacska et al., 2018). Vegetation growth and senescence can also obscure SAR backscatter when detecting soil surface moisture conditions, but the impact of vegetation can be corrected with phenological models such as simple sine curve equations (Lees et al., 2021a).

Assessment towards pristine-like conditions requires a reference (Gann et al., 2019), optimally historical RS data on pre-drained conditions. However, this is rarely possible, since many drainage activities on boreal peatlands have been implemented before the launch of the first RS satellite missions such as Landsat in the 1970s. Historical airborne photographs often give the longest-term perspective, but their poor quality, georeferencing challenges, and irregular timing of data

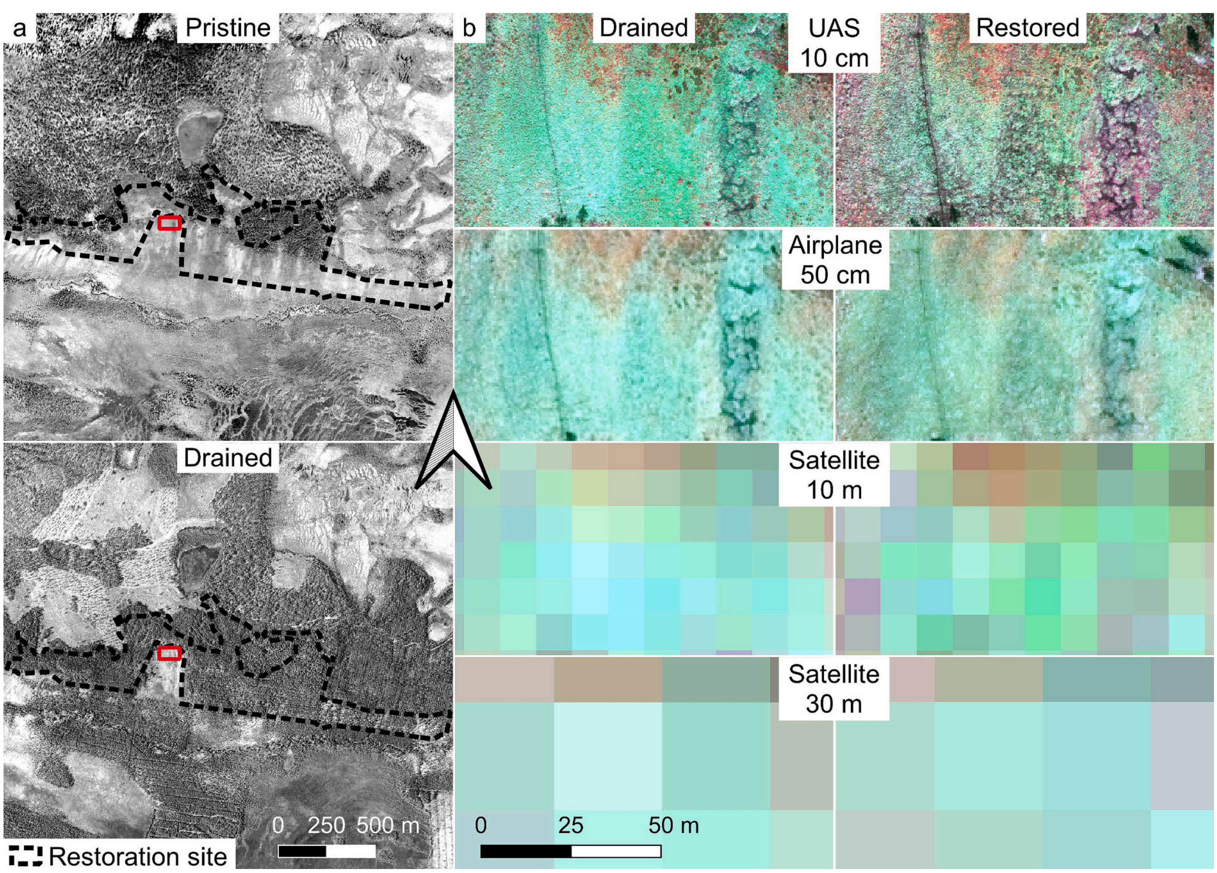

Fig. 2. a) Historical pre-drainage (1950), and pre-restoration (2008) black-and-white aerial orthoimages (National Land Survey of Finland) from a sloped fen site with seepage in Northern Finland (65.053°N, 27.158°E), restored in Oct 2019. The site was drained for forestry in the 1970s, and the tree growth was heavily intensified thereafter. Even the non-ditched area studied in b (red rectangle in a) was suffering from the upslope drainage activities. b) Effect of spatial resolution on reflecting typical surface moisture heterogeneity on the open fen. NIR false-colour images are presented before and after the rewetting. Recovered seepage (dark pixels) and increased surface moisture (purplish pixels) can be identified after the restoration. When using coarser resolution data, the more detailed features of the peatland remain undetected. UAS multispectral data (Drained state mapped in Aug 2019, restored in Aug 2020) was collected by Pasi Korpelainen (UEF Dronelab). Open access aerial photographs (Jun 2019, Jun 2021) are from the National Land Survey of Finland. Spaceborne data includes Sentinel 2 (10 m, Aug 2019, Aug 2020) and Landsat 8 (30 m, Jun 2019, Jun 2020). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

acquisition disrupt the systematic use (Bhattacharjee et al., 2021). Similarly, restoration monitoring should be initiated before rewetting to determine the degraded indicator states (Menberu et al., 2016). Without access to pre-drained or pre-restored datasets, simultaneous monitoring of restored, degraded and pristine reference sites (Before-After-Control-Impact) is an approach to apprehend the development of the restoration indicators and to distinguish the restoration efforts from the natural variation and, e.g., the impacts of climate change (Elo et al., 2024; Haapalehto et al., 2017). Additionally, simulation models (Gann et al., 2019; Langanke et al., 2007) can also be used for change detection, when there is a need to monitor old restoration sites. Eventually, there is no universal guideline for how small a difference between the restored and reference conditions can conclude the success of restoration. This is site or ecosystem and actor specific. As the pre-drainage condition cannot be fully recovered on peatlands in a short term, reversing their degradation and regaining the ecological functionality is recommended to be aimed (United Nations, 2021). Hopefully, future research and political guidance will further empower defining the restoration success.

5.4. Quality management

All RS methods need conversant quality control. It is particularly important when only raw data is available, or when the peatland ecosystem researcher takes the full role of the operator instead of RS professionals, as often is the case with UAS. A vital requirement for precise change detection is high-accuracy georeferencing, i.e., the pixels compared must represent the same location each time. Furthermore, while the signal of passive sensors typically originates from the sun, the impacts of atmospheric conditions and travel routes must be considered by careful radiometric calibration and data normalization (O'Connell et al., 2013). In other words, the measured signal (e.g., tones and brightness in the case of RGB data) must remain the same with no dependence on illumination properties nor the sensor. Even when using active sensors, preprocessing (e.g., speckle-filtering of SAR data) must be included before further analysis (Bourgeau-Chavez et al., 2017).

Validating the RS results with ground reference data is critical for scientific research. While practice-level restoration work prefers small efforts in the field, also it should always include the acquisition of at least some validation data due to the uncertainties of RS data. Some methods always require ground measurements for calibration (e.g., CH_4 extrapolation, Tagesson et al., 2013), while others can be significantly improved by them (e.g., supervising a land-cover classification, Reif and Theel, 2016), and in some cases, field observations are required to transform RS observations to absolute values (e.g., relative versus absolute soil surface moisture, Wigmore et al., 2019). In many cases, it is sufficient to visualize the spatial distributions of wetness, without the need to know the exact values of water content. However, determining absolute values increases the comparability of results between sites. In some cases, field calibration and validation data can be partially replaced by visual interpretation of UAS datasets (e.g., Keränen et al., 2024).

The unit scale of the results should remain the same to ensure comparability in the time series and between-site analyses. Besides geometric and radiometric calibration, this means considering the factors impacting the signal, other than the variable of interest, such as vegetation development during moisture monitoring (Lees et al., 2020). Generally, ground referencing should be conducted concurrently with remote sensing campaigns. Some information can be collected nearly continuously such as WT data with automated loggers and GHG exchange data with eddy covariance, but for more intensive ground reference monitoring such as manual WT measurements or detailed vegetation inventories, suitable time-points could be, e.g., 2, 5, and 10 years after restoration as guided by Elo et al. (2024). In all cases, remote sensing data should be regularly calibrated with reference data, and the phenological and between-year changes should be accounted for when matching remote sensing and ground reference data.

5.5. Limitations, knowledge gaps, and outlook

RS technology has developed rapidly in the past decades. While older peatland RS research focused mostly on optical satellite data, newer technologies such as SAR, LiDAR, and UAS have been studied increasingly during the latest years (Chasmer et al., 2020b). Abdelmajeed and Juszczak (2024) studied the challenges and limitations of RS applications in northern peatlands in their systematic review. They concluded the largest knowledge gaps to include, e.g., the lack of i) field data, particularly, in areas with poor ground access, ii) automated analysis algorithms if RS monitoring was implemented in large-scale, and iii) quantitative error assessment methods. Based on the views presented in this paper, the largest challenge of RS monitoring remains in complex simultaneous ecohydrological processes on peatlands. While only one RS subject at time is under observation, the impact of other processes on the recorded signal needs recurrent calibration, which usually requires also comprehensive ground-based monitoring (Isoaho et al., 2024a). Thus, RS can never completely replace ground-based measurements, although it can supplement conventional knowledge at various levels. Furthermore, many RS methods (e.g., trapezoid models, Isoaho et al., 2024b) work only on specific site conditions and cannot thus be directly transferred to other sites or even other parts of the site if comparable results are expected. Methods with such parametrization requirements still enable drawing location-specific conclusions but not at a regional or national level. For large-scale monitoring, universally comparable RS methods still need development. However, the high between-site variation in peatland ecosystems and restoration success hamper the development of universal models (e.g., Elo et al., 2024; Räsänen et al., 2022).

Specifically, shallow peatlands typically include tree cover in their pristine state, which has often been intensified after drainage for forestry. Tree cover presents a major challenge for RS, as i) it partly conceals the peatland surface of interest, attenuating or breaking the signal (Iglhaut et al., 2019), ii) it influences evapotranspiration estimations crucial for peatland hydrology (Spieksma et al., 1997), and iii) it creates disturbing shadows for high to ultra-high spatial resolutions, which appear differently on each campaign (Pasher and King, 2009; Reif and Theel, 2016). Not only do trees obstruct the view of objects of interest, but they impact the data, e.g., producing bias to RS-based hydrological estimation (Millard and Richardson, 2018) and reducing the accuracy of SfM (Ikkala et al., 2022) and LiDAR (Korpela et al., 2009) DTMs. In the densely tree-covered areas, conventional ground-based surveys, also ground-based RS (such as handheld or field-installed cameras, spectroradiometers and terrestrial LiDAR) will remain as primary methods. However, under-canopy UAS SfM campaigns may be possible in the future after improvements in collision avoidance and GNSS-denied navigation (Krisanski et al., 2020). On forestry-drained restoration sites in specific, tree felling might make the peatland surface visible if the acquisition can be initiated after the felling but before rewetting (Ikkala and Similä, 2024). However, not enough trees are necessarily removed, and if only ditch benches are cleared, UAS mapping should be used to achieve sufficient data resolution for these narrow corridors.

Even when the peatland surface is clearly visible, not everything relevant can be mapped using RS. For instance, spectral indices typically work best with data of specific species and are weaker when explaining a blend of both Sphagnum and vascular plants (Kalacska et al., 2015; Lees et al., 2018; Peichl et al., 2015). Furthermore, distinguishing between different moss species is sometimes crucial for monitoring the success of the targeted peatland type, as different species have diverging habitat preferences (Similä et al., 2014). Yet, the determination of such mosses, for instance, requires macro or microscopic observations (Elo et al., 2024), which is unattainable with RS. In addition, the underground hydrological connections are often complex due to variance in peat properties and diverse surrounding mineral soil layers, and GW might discharge relatively far away from the main aquifer (Jaros et al., 2019).

This underground hydrology remains mostly hidden from RS (Ikkala et al., 2022). Thus, the RS of subsoil variables relies on their connections with surface properties such as capillarity for observing WT depth through soil surface moisture.

Space agencies internationally are planning several missions with potential for enhancing spaceborne peatland restoration monitoring (Table 7). First experiences of spaceborne LiDAR have already been gathered with the ICESat-2 mission. While the data is not comparable with airborne LiDAR, it can still enable large-scale estimates of, e.g., tree stand structure development (Neuenschwander and Magruder, 2019). The ESA BIOMASS mission will introduce the first ever P-band SAR on spaceborne platform (Quegan et al., 2019). The P-band SAR, having a longer wavelength than common SAR sensors (X, C, and L-bands), can penetrate deeper into the vegetation or soil, providing new insights to tree-stand structure or deeper soil moisture estimation (Kornelsen and Coulibalya, 2013). Other new SAR sensors that can be utilized in restoration monitoring include NASA-ISRO SAR (NISAR) that includes both L and S bands and ESA L-band ROSE-L (eoPortal, 2024; NASA, 2025). In addition, hyperspectral data has been used marginally to study peatlands despite their potential (Abdelmajeed and Juszczak, 2024; Arasumani et al., 2023; Wolff et al., 2024). While most hyperspectral research has focused on airborne RS (Arroyo-Mora et al., 2018; Middleton et al., 2012; Pang et al., 2024; Räsänen et al., 2020b), future satellite missions (e.g., ESA CHIME and Landsat Next) promise data with spaceborne advantages, including higher temporal resolution and larger monitoring extent (McPartland et al., 2019). Nevertheless, some studies have indicated the limited added value of hyperspectral when compared to multispectral data (Pang et al., 2024). Furthermore, also spaceborne CH_4 monitoring will be enabled with the Methane Remote LiDAR Mission planned to launch in 2028 (Bousquet et al., 2018).

UAS technology can also enable production of novel types of data. Like the UAS GPR measurements (Henrion et al., 2025) and GHG concentration sampling (Lampert et al., 2020; Scheller et al., 2022) presented to be moved to the flying platforms, also surface water quality can be sampled with little effort for large, unattained peatlands (Koparan et al., 2018). Also, LiDAR sensors have been taken in use onboard UAS to introduce flexible operation possibilities and advanced resolutions to this canopy-penetrating RS method (Kalacska et al., 2021). In addition, soil surface moisture and vegetation communities have been studied using airborne SAR (Wang et al., 2023) that would enable mapping also on rainy or foggy days. For optical spectrum, the high potential related to the sensitivity of SWIR wavelengths for soil surface moisture (Harris and Bryant, 2009; Turner et al., 2024) requires future attention. SWIR sensors have been available for airborne platforms for some time already, but the use of such sensors has remained relatively limited. UAS swarms could provide an approach for producing instant information on large extents, e.g., when probing GHGs (Zhao et al., 2024). Similarly, simultaneous multi-camera exposure using a UAS swarm (Structure-from-Swarm instead of SfM) could help solve the uncertainties related to long UAS campaigns such as changing illumination conditions and swaying trees.

In general, as restoration monitoring or RS calibration requires ground-based approaches, these research designs could be planned assisted with more general RS data by recognizing the critical locations for detailed monitoring. For instance, the failed restoration constructions could be identified with spaceborne soil moisture data for focusing the UAS or field campaigns on where sufficient rewetting was not achieved (Isoaho et al., 2025). Also, UAS swarms could be used to first map larger extents with less details before focusing the detailed mapping on where it is needed.

Finally, besides restoration monitoring, rapidly developing RS methods can provide unprecedented tools for evaluating restoration needs, selecting sites and planning measures (Cordell et al., 2017), and in specific, simulating the locations of dams (Karaśkiewicz and Wójcik, 2024). In more general terms, RS data can also help engaging stakeholders of restoration projects by providing unbiased, spatial understanding on the degradation status and restoration impacts (Gann et al., 2019).

6. Conclusions

There is growing interest in implementing RS methods in peatland restoration, particularly for assessing changes in soil conditions, hydrology, vegetation, and related ecohydrological processes. Increasing restoration activities require unbiased spatial data on the implementation success to understand its impacts, improve the efficiency of measures and further develop the restoration methods. RS can flexibly provide this information in various spatial and temporal scales and coverages. While RS data collection is typically less time-consuming than traditional field-based monitoring, the overall workload may be substantial when data processing and analysis efforts are considered. Although RS does not always achieve the local accuracy of point-based methods, it enables spatially continuous assessments and can reveal patterns and heterogeneity that remain hidden with the conventional approaches. However, RS methods also have limitations, particularly in areas with dense tree cover or site conditions vary temporally or spatially. A key challenge moving forward is the development of RS methods that yield universally comparable results across sites and conditions. Furthermore, several RS technologies presented are still in their infancy requiring further testing in varying conditions and future satellite missions and increased use of UASs provide even more data that can be utilized in restoration monitoring. Nevertheless, many methods have already matured owing to scientific research on resolving the challenges. These numerous applications can be implemented by peatland practitioners without much experience on RS. The reality, however, often is to aim at implementing the most recent methods, which drives the use of sophisticated expert analyses with numerous intermediate steps. While large volumes of RS data are now available — and more can be generated with relatively low effort — the full potential of these technologies will only be realized through closer collaboration between researchers and practitioners. Such cooperation is essential to ensure that RS efforts are targeted towards the most pressing restoration objectives and are implemented in ways that support practical decision-making.

CRediT authorship contribution statement

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Table 7
Examples of remote sensing methods with future potential for peatland restoration monitoring. Restored peatland sites are marked as **yellowed bold**, non-peatland sites as *greyed italic*.

Platform	Subject	Method	Source	Site type	Location
Satellite	Deeper soil moisture estimates	P-band SAR	Quegan et al. 2019	Forests	French Guiana, Indonesia, Sweden, Gabon, Ghana
	Advanced peatland vegetation mapping	Spaceborne hyperspectral	Arasumani et al. 2023	**Rewetted riverine percolation fens**	Germany
	Large-scale changes in tree stand structure	Spaceborne LiDAR	Neuenschwander & Magruder 2019	Boreal forest, tropical forest, and semi-arid woodlands	Canada, Brazil, Botswana
	Large-scale CH_4 monitoring	Spaceborne LiDAR	Bousquet et al. 2018	-	-
	Large-scale monitoring for focusing UAS and ground monitoring	Spaceborne monitoring	Isoaho et al. 2025	**Restored open peatlands, mostly aapa mires**	Finland
UAS	Soil surface moisture and vegetation structure	UAS SAR	Wang et al. 2023	Inland river delta including perched wetland basins	Canada
	Soil surface moisture and vegetation	UAS SWIR hyperspectral	Turner et al. 2024	Antarctic moss bed	Antarctic
	Peatland surface properties under dense canopy	Under-Canopy UAS Photogrammetry	Krisanski et al. 2020	Native regrowth eucalyptus pulchella forest	Australia
	Water quality	UAS water sampling	Koparan et al. 2018	Pond	USA
	Peatland 3D structure	UAS LiDAR	Kalacska et al. 2021	Ombrotrophic bog	Canada
	GHG probing, instant SfM and large-scale mapping	Autonomous self-recharging UAS swarms	Zhao et al. 2024	Anthropogenic gas emission sources	China

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.rse.2025.115093.

Data availability

No data was used for the research described in the article.

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