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Monitoring changes in boreal peatland vegetation after restoration with optical satellite imagery

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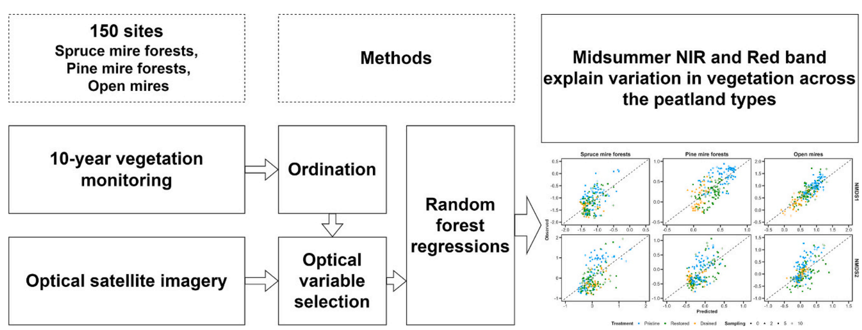
HIGHLIGHTS

- We assess post-restoration changes in peatland vegetation with satellite imagery.
- Different peatland types should be monitored with different optical variables.
- Floristic gradients of pine mires forests and open mires can be remotely sensed.
- Monitoring vegetation development is feasible in peatlands with little or no trees.

GRAPHICAL ABSTRACT



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ABSTRACT

Restoration can initiate a succession of plant communities towards those of pristine peatlands. Field inventory-based vegetation monitoring is labour-intensive and not feasible for every restored site. While remote sensing has been used to monitor hydrological changes in peatlands, it has been less used to monitor post-restoration changes in vegetation composition. We utilised vegetation inventories from Finnish peatland monitoring network containing 10-year before-after-control-impact monitoring data from 150 peatland sites, representing three peatland types (spruce mire forests, pine mire forests, open mires), and optical observations from Landsat 5–9 and Sentinel-2 satellites. We employed non-metric multidimensional scaling (NMDS) to produce floristic gradients, representing wetness and productivity, from the vegetation data. We constructed random forest regression models with NMDS dimensions, i.e. floristic gradients, as response variables and satellite imagery variables as the predictors. Our results show that the floristic gradients in different peatland types should be monitored with different satellite imagery variables. However, midsummer NIR and red band consistently explain variation in the gradients in all peatland types. Our results indicate that the gradients and the post-restoration changes in them can be modelled with reasonable accuracy in open mires and sparsely treed pine mire forests but not in

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densely treed spruce mire forests. We suggest that optical satellite imagery can serve as a proxy for assessing the post-restoration vegetation changes in peatlands with little or no trees.

1. Introduction

Peatlands provide important ecosystem services, harbour unique biodiversity and store large carbon stocks (Chapman et al., 2003; Bonn et al., 2014; Joosten et al., 2016). The degradation of peatlands mainly due to land use activities has caused major negative impacts on these functions (Marttila et al., 2020). Currently, around 11 % of the world's peatlands are degraded (Leifeld and Menichetti, 2018) and the situation is particularly severe in the European Union, where half of the peatlands are already degraded (European Commission, 2020). In the boreal zone, drainage for forestry and agriculture is the main reason for peatland degradation (Minkkinen et al., 2008). The drainage for forestry lowers the water table level within the peat (Price et al., 2003; Haapalehto et al., 2014), and leads to a shift in plant communities towards drier, more mineral soil forest type of vegetation (Laine et al., 2006; Maanavilja et al., 2014).

Restoration can significantly improve the condition of degraded peatlands and re-activate their natural functions (Rana et al., 2024). Restoration in boreal forestry-drained peatlands aims to raise the water table, allow regeneration of peatland vegetation and initiate formation of new peat. This process involves rewetting the drained areas through damming and infilling the drainage channels and in some cases, removing trees that have grown after drainage (Andersen et al., 2017). Restoration has fast effect on hydrological properties, such as raising the water table (Haapalehto et al., 2011, 2014; Menberu et al., 2016; Isoaho et al., 2024).

Restoration is also successful in initiating the recovery of vegetation towards pristine-like vegetation (Laine et al., 2011; Haapalehto et al., 2011; Maanavilja et al., 2014; Kareksela et al., 2015; Haapalehto et al., 2017; Elo et al., 2024b). However, vegetation in restored sites remains dissimilar compared to pristine sites 10 years after restoration (e.g. Haapalehto et al., 2011; Elo et al., 2024b), and restoration may not return the peatlands fully to their pristine condition even after 30 years (Kreyling et al., 2021). Hence, long-term monitoring is needed to capture the full spectrum of vegetation changes and challenges associated with restoration efforts which may not be evident immediately after the restoration. However, comprehensive vegetation monitoring is labour-intensive and not feasible for every restored sites. Thus, the development of new, more automated monitoring methods is needed.

Remote sensing (RS) techniques have been increasingly utilised for upscaling the vegetation observations across spatial and temporal scale in peatlands (Harris et al., 2015; Beyer et al., 2019; Räsänen et al., 2019, 2020; Pang et al., 2023). Usually, optical imagery has been utilised, and the importance of near-infrared (NIR) region has been emphasized (Harris et al., 2015; Räsänen et al., 2020; Kolari et al., 2022) due its association with vegetation patterns, and being able to separate different plant species, habitats and peatland types (Middleton et al., 2012; Salko et al., 2023). Typically, it has been suggested to use fine spatial resolution imagery captured by uncrewed aerial vehicles (UAVs) due to the spatially heterogeneous structure of peatlands and because the vegetation inventories are usually conducted on small, often 1 m^2 or smaller plots (Räsänen and Virtanen, 2019; Räsänen et al., 2020; Wolff et al., 2023; Steenvoorden and Limpens, 2023). This makes coarse resolution (>30 m) imagery from satellites less usable. However, the limited temporal coverage of fine-resolution imagery from UAVs, crewed aircrafts or satellites makes their use impractical for long-term monitoring. Instead, medium resolution satellite imagery (10–30 m pixel size), such as Landsat 5–9 (L5–9) and Sentinel-2 (S2) has been successfully used for vegetation change detection in peatlands (Kolari et al., 2022) and proven effective in detecting seasonal and spatial vegetation patterns (Bhatnagar et al., 2020; Garisoain et al., 2023; Pang et al., 2023).

RS-based vegetation studies in peatlands often focus on producing categorical maps of land cover, habitat or vegetation types (e.g. Räsänen and Virtanen, 2019; Steenvoorden et al., 2023). While some studies have shown species-level upscaling possibilities with RS data (Kalacska et al., 2013; Husson et al., 2014; Bergamo et al., 2023), more prominent approaches have been predicting groups of species such as plant functional groups or plant communities (Harris et al., 2015; Räsänen et al., 2020; Steenvoorden et al., 2023; Steenvoorden and Limpens, 2023; Wolff et al., 2023). It has been argued that continuous vegetation maps offer a more realistic depiction of vegetation patterns than categorical maps (Rocchini, 2014; Räsänen et al., 2019). Particularly, floristic gradients derived from vegetation ordination analysis provide insights into species distribution along ecological and environmental gradients such as wetness or nutrient status (Harris et al., 2015) which are often the focus of restoration efforts (Menberu et al., 2016, 2017). Ordination analysis is a widely used method in community ecology to simplify complex species presence or abundance data into gradients that explain a large part of the variation in the data (e.g. Anderson, 1971; Verniest and Greulich, 2019). Floristic gradients offer possibility to determine similarities and differences between plots or sites in a continuous, multidimensional space (e.g. Räsänen et al., 2020), and for restoration assessment, they can show how plant communities in restored sites become less dissimilar to communities in drained sites state and more similar to those of pristine sites state (Elo et al., 2024b). In peatlands, the gradients that explain most of the variation in the data are typically related to wetness and productivity (Pakarinen and Ruuhijärvi, 1978; Middleton et al., 2012; Räsänen et al., 2020).

In RS studies related to peatland restoration, Ball et al. (2023) have demonstrated that on a large scale, spectral properties of restored peatlands are approaching peatlands with a good ecological condition in a 25-year timescale. A few studies (e.g. Kolari et al., 2022; Steenvoorden et al., 2022; Talvitie et al., 2023) have shown that long-term changes in peatland microforms or habitat types can be monitored with RS data. Additionally multiple studies have indicated that hydrological changes following restoration can be assessed with RS data (Räsänen et al., 2022; Ikkala et al., 2022; Burdun et al., 2023; Isoaho et al., 2023, 2024). Nevertheless, to the best of our knowledge, no studies have utilised RS data for detecting long-term and frequently monitored post-restoration vegetation changes.

In this study, we hypothesize that optical satellite imagery can be effectively used to monitor post-restoration changes in peatland vegetation. To examine this hypothesis, we use extensive and widespread peatland restoration vegetation inventory in Finland (Elo et al., 2024a, 2024b), utilising a before-after-control-impact scheme (Christie et al., 2020). Our specific objectives are to: (1) identify the most suitable optical satellite variables for modelling the continuous floristic gradients of boreal spruce mire forests, pine mire forests and open mires with different treatments, (2) assess how well the floristic gradients can be predicted with optical satellite variables, and (3) determine the feasibility of using optical satellite variables to monitor temporal changes in floristic gradients.

2. Materials and methods

2.1. Finnish peatland monitoring network

We utilised field data from the peatland monitoring network established by Metsähallitus Parks & Wildlife, Finland (Fig. 1). The network comprises 150 monitoring sites across three peatland types: spruce mire forests (n = 49), pine mire forests (n = 51), and open mires (n = 50), each undergoing different treatments: pristine (n = 60), restored (n =

60), and drained (n = 30). Additionally, the sites have been classified with rich or poor productivity based on their nutrient level and species composition by the botanical experts of Metsähallitus Parks & Wildlife, Finland. The pristine and restored sites were established between 2006 and 2012, while all drained sites were established in 2012. The sites have been used to monitor changes in vegetation, water table and porewater variables. The data obtained from the network is comprehensive and enables large-scale studies on peatland vegetation, hydrology and biogeochemistry, and their responses to the restoration (Menberu et al., 2016, 2017; Räsänen et al., 2022; Burdun et al., 2023; Elo et al., 2024b). From the original 151 site network, one site (Id 2; Elo et al., 2024a) have been removed due the site being destroyed after first vegetation sampling.

Spruce mire forests are characterised by relatively dense canopy. Based on the Finnish multi-source National Forest Inventory data (Natural Resources Institute Finland, 2023), the pristine sites of the monitoring network have average tree coverage of 68 %. Tree cover is usually dominated by *Picea abies* or *Betula pubescenes*. The water table in these mires can reach depth of over 50 cm and in drained sites, even up to 1 m during midsummer (Menberu et al., 2016), resulting in ground vegetation that includes both peatland and mineral soil forest plant species such as *Vaccinium myrtillus* and *Maianthemum bifolium*. Pine mire forests have sparser tree cover (average of 26 % in the pristine sites of the network; Natural Resources Institute Finland, 2023) and the typical tree species include *Pinus sylvestris* and *Betula pubescens*. Their ground layer is characterised by different *Sphagnum* mosses and vascular plants such as *Eriophorum vaginatum* and *Rhododendron tomentosum*. The water table of pine mire forests is typically closer to the surface compared to spruce mire forests, but in drained sites the water table is similar to pristine or even drained spruce mire forests (Menberu et al., 2016). Open mires have almost non-existent tree cover (average of 4 % in the pristine sites of the network; Natural Resources Institute Finland, 2023) and ground vegetation is characterised e.g. by *Sphagnum* and *Carex* species that are adapted to wet conditions. Pristine open mires are typically wetter than spruce or pine mire forests, and the water table can rise on the peatland surface during spring and autumn floods. Additionally, seasonal water table variation in pristine open mires is lower compared to the other two types (Menberu et al., 2016). However, in drained sites, the water table can be similar to pine mire forests, and in well-drained sites, similar to spruce mire forests (Menberu et al., 2016).

Vegetation monitoring at restored sites was conducted before restoration, and again two, five, and ten years after restoration. For pristine and drained sites, a similar monitoring schedule was followed, although the actual number of years between the samplings may differ. Each site includes ten permanent 1 m^2 plots (Fig. 1) within which the percent cover (%-cover) of every vascular plant and moss species has been visually estimated by the botanical experts of Metsähallitus Parks & Wildlife, Finland. The data from those ten plots were aggregated to represent the average %-cover of the species at each of the 150 study sites. There have been some uncertainties with identifying in particular *Sphagnum* species, which is why some species have been grouped to avoid uncertainty due to misidentification. A more detailed explanation of the vegetation monitoring methodology is provided in Elo et al. (2024b).

2.2. Remote sensing data

We utilised multitemporal optical S2 and L5–9 satellite imagery,

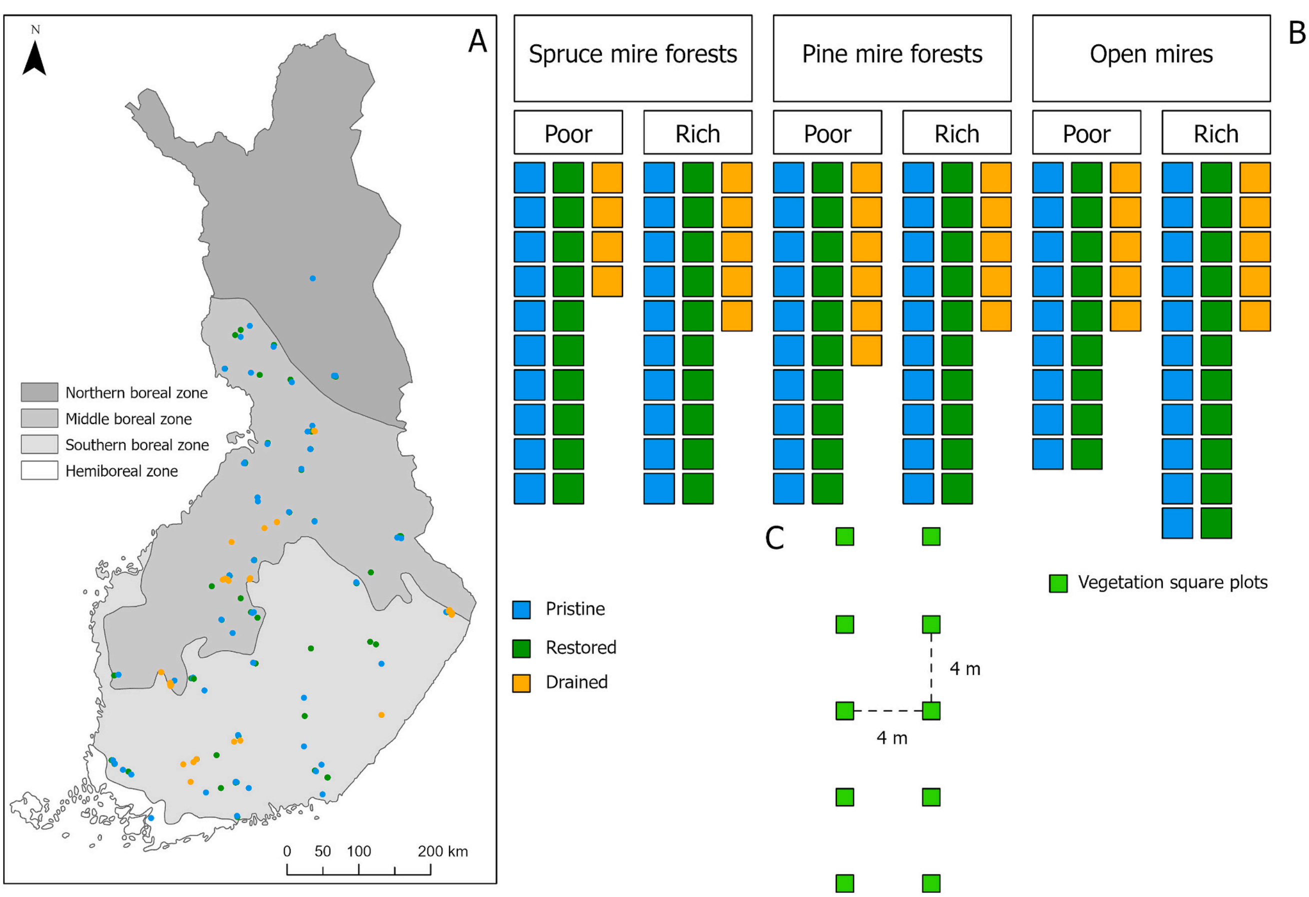

Fig. 1. Finnish peatland monitoring network. Map demonstrates locations of the monitoring sites. Second chart demonstrates number of monitored sites within peatland types and productivity (poor and rich), colours of peatland treatments are same for map (A) and chart (B). Chart C demonstrates how the vegetation inventory is conducted within the sites, i.e. two parallel lines with five 1 m^2 plots and the distance between the plot edges is four metres.

accessed and processed in Google Earth Engine (Gorelick et al., 2017). First, we filtered out imagery with cloud cover exceeding 30 %. Leftover clouds, cloud shadows and snow were masked using the Scene Land Cover and Quality Assessment pixel classification for S2, and L5–9, respectively. Second, we improved cross-usability by harmonising all imagery to L8–9 Operational Land Imager sensor specifications using the coefficients and slopes proposed by Roy et al. (2016) for L5 and L7, and by Zhang et al. (2018) for S2. Third, we utilised six spectral bands and calculated eleven spectral vegetation and wetness indices (Table 1), broadly utilised in hydrological and ecological peatland studies from the S2 and L5–9 imagery (Table S1). We extracted the data for the years 2000–2023 with area-weighted mean values for each RS band and index for 15 m radius buffers. The centre of each buffer located in the middle of parallel lines between the vegetation inventory plots (see Fig. 1), i.e. only one buffer per site was used and it contained all the vegetation inventory plots of the site. We removed all obvious outliers (STR $\geq$ 10, EVI or SAVI outside of 0–1 range) from the dataset. Lastly, for dates with multiple RS observations at one site, we calculated the mean value of these observations.

We further processed the RS data to make it more comparable with the vegetation data and across different sites, as well as to minimise possible errors from residual clouds and cloud shadows. This involved calculating annual medians for two distinct time windows: early summer (1 May–15 June) and midsummer (1 July–15 August) to capture different hydrological (Sallinen et al., 2023; Isoaho et al., 2024) and phenological (Juutinen et al., 2017; Pang et al., 2023) moments within growing season. To further minimise the multiyear variation and increase RS data availability, we calculated the so-called sampling medians (median value from annual medians used for sampling calculations) from annual medians utilising years specified in Table 2. For 0-year sampling, we used satellite data from five years prior the actual sampling year as these rely solely on older L5 and L7 products, which have a sparser revisit time compared to L8–9 and S2. For the rest of samplings, we used a three-year period centred around the actual sampling year (Table 2). Total number of utilised observation dates used per sampling medians varies between sites, but generally image availability is more limited prior sampling 10 for pristine and restored sites, and prior sampling 5 for drained sites. These latter samplings always include S2, unlike older samplings that rely solely to L5–8 (Fig. 2).

Table 2
Used years for calculating remote sensing sampling medians from annual medians.

Vegetation sampling	Remote sensing data utilised (difference from the years of vegetation sampling)
0-year[a]	−1, −2, −3, −4, −5
2-year	−1, 0, +1
5-year	−1, 0, +1
10-year	−1, 0, +1

[a] We excluded the sampling year in the 0-year sampling calculations as sometimes the actual restoration month is unknown. Inclusion of 0-year could have resulted in post-restoration observations to be included if vegetation sampling was conducted in early summer and restoration conducted in midsummer of the same year.

2.3. Statistical analyses

We determined observed floristic gradients with non-metric multidimensional scaling (NMDS; Kruskal, 1964) which produces continuous and interpretable gradients that can be visualised in a multidimensional space (e.g. Harris et al., 2015). We calculated the NMDS axes from the site-averaged vegetation %-cover data containing all peatland types, thus describing the broad-scale vegetation patterns. We applied Wisconsin double standardization and square root transformation to the data, calculated the distance matrix with Bray-Curtis distances (Bray and Curtis, 1957) and tested the stress level with 20 random starts.

Table 1
Used remote sensing bands, vegetation indices, and wetness indices with equations. Justifications for bands and indices are in Table S1.

Variable	Abbreviation	Equation	Reference
Blue reflectance	Blue		
Green reflectance	Green		
Red reflectance	Red		
Near-infrared reflectance	NIR		
Shortwave infrared band 1 reflectance	SWIR1		
Shortwave infrared band 2 reflectance	SWIR2		
Shortwave infrared transformed reflectance	STR	$\frac{(1-SWIR1)^2}{2*SWIR1}$	Sadeghi et al., 2015
Normalised Difference Vegetation Index	NDVI	$\frac{NIR-Red}{NIR+Red}$	Tucker, 1979
Enhanced Vegetation Index	EVI	$2.5*\frac{NIR-Red}{NIR+6*Red-7.5*Blue+1}$	Liu and Huete, 1995
Soil Adjusted Vegetation Index	SAVI	$1.5*\frac{NIR-Red}{NIR+Red+0.5}$	Huete, 1988
Tasseled cap Greenness[a]	TCGreenness	$Blue*(-0.2941)+Green*(-0.243)+Red*(-0.5424)+NIR*0.7276+SWIR1*0.0713+SWIR2*(-0.1608)$	Kauth and Thomas, 1976; Crist and Cicone, 1984
Normalised Difference Water Index	NDWI	$\frac{Green-NIR}{Green+NIR}$	McFeeters, 1996
Modified Normalised Difference Water Index	MNDWI	$\frac{Green-SWIR2}{Green+SWIR2}$	Xu, 2006
Normalised Difference Moisture Index	NDMI	$\frac{NIR-SWIR1}{NIR+SWIR1}$	Gao, 1996
Normalised Difference Moisture Index 2	NDMI2	$\frac{NIR-SWIR2}{NIR+SWIR2}$	Gao, 1996
Tasseled cap Wetness[a]	TCWetness	$Blue*0.1511+Green*0.1973+Red*0.3283+NIR*0.3407+SWIR1*(-0.7117)+SWIR2*(-0.4559)$	Kauth and Thomas, 1976; Crist and Cicone, 1984
Tasseled cap Angle[b]	TCAngle	$arctan\left(\frac{TCGreenness}{TCBrightness}\right)$	Powell et al., 2010

[a] Landsat OLI tasseled cap coefficients (Baig et al., 2014) are used because the data are harmonised to the OLI sensor.
[b] TCBrightness = Blue * 0.3029 + Green * 0.2786 + Red * 0.4733 + NIR * 0.5599 + SWIR1 * 0.508 + SWIR2 * 0.1872.

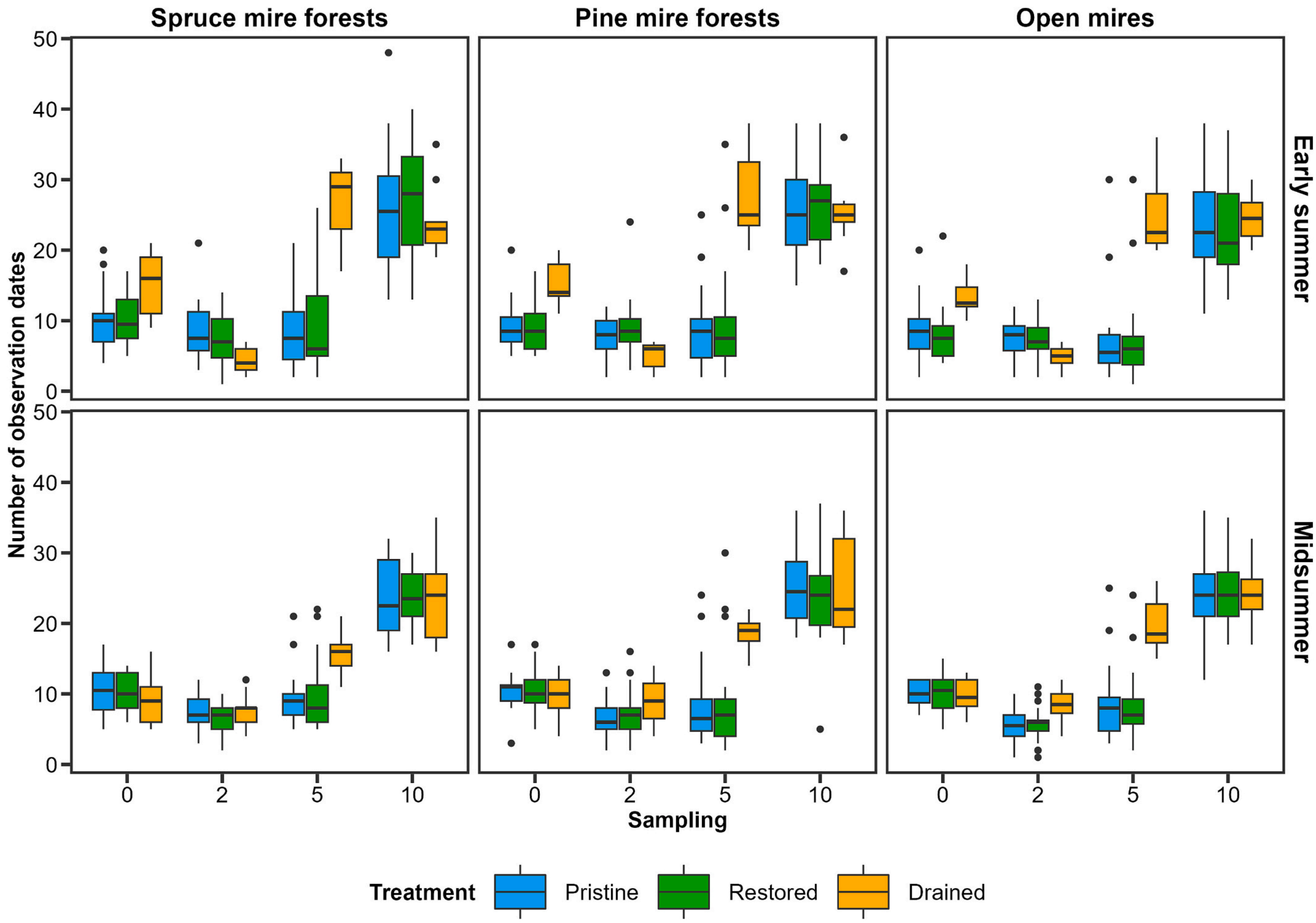

Fig. 2. Number of observation dates per peatland type and treatment used for calculation of sampling medians. For some observation dates, there are multiple satellite images available. In these cases, we calculated the mean value of the observations. Early summer refers to 1 May to 15 June and Midsummer to 1 July to 15 August. Drained sites have more observation dates in sampling 5 because all of them were established in 2012, meaning that they always include Sentinel-2 images from 2017 and 2018. In contrast, most of the pristine and restored sites rely solely on Landsat 7 and 8 for the same sampling.

Given that a two-dimensional ordination resulted in an acceptable stress level (~0.14) while being ecologically meaningful (Figs. S1, S2), we refrained from adding more dimensions, considering the challenges in visualising or interpreting three or more dimensions. First floristic gradient (NMDS1) represented wetness gradient and second floristic gradient (NMDS2) was connected to productivity of the sites (Figs. S1, S2).

To predict the floristic gradients with RS data, we used random forest regression (Breiman, 2001). We utilised all the RS variables (Table 1) as predictor variables, incorporating data from both early and midsummer periods, while the floristic gradients (NMDS axes) were the response variables. The simultaneous use of both periods is based on the fact that multitemporal imagery can enhance the predictive accuracy of vegetation community models (Dudley et al., 2015; Räsänen et al., 2020), and this also produced more accurate models based on our preliminary tests. The modelling was conducted separately for spruce mire forests, pine mire forests and open mires to better capture variation within peatland type specific treatments. We did not use site productivity information for further peatland type specification as this would have halved the peatland type specific data and made the models less stable. We opted for default random forest parameter settings as hyperparameter tuning has led only to minor improvements in RS applications (Belgiu and Drăguţ, 2016; Probst et al., 2019); thus, we set the number of trees to 500 and the number of variables tested at each tree node to 1/3 of available variables. Before implementing the final models, we conducted peatland type specific (i.e. spruce mire forests, pine mire forests, open mires) automated variable selection with Variable Selection Using Random Forests (VSURF; Genuer et al., 2015). This step was taken to determine the most suitable RS variables for modelling, to avoid overfitting, and to boost the regression performance. VSURF utilises a three-step procedure (thresholding, interpretation, prediction) with nested random forest models and variable importance metrics to remove irrelevant and redundant variables from the dataset. We used default parameters of VSURF with the exception that we increased number of forests in each step from the default value of 10 to 20 to further eliminate randomness in the variable selection.

We assessed model performance separately for spruce mire forests, pine mire forests and open mires to evaluate the differences in the model performance between peatland types. This evaluation utilised out-of-bag estimation (approximately 1/3 of data is left for validation when building each tree), which provides a conservative estimate of model fit in RS applications (Clark et al., 2010). We calculated the % explained variance (Pseudo $R^2 = 1 -$ mean square error / variance of response variable) and normalised root mean square error (nRMSE; RMSE divided by the range of response variable values) to evaluate model performances. We repeated the models 100 times and calculated the mean of evaluation metrics for the full variable set and the VSURF determined subset to see if variable selection improved the performance. We also extracted variable importance from the subset models utilising increase in mean square error statistic for each model iteration separately, summing them, and normalising the results between 0 and 100 %.

We separately assessed temporal changes in the observed and predicted NMDS axes to determine if restoration effect could be determined from the axes. Here, we calculated peatland type and treatment specific averages over samplings 0 and 10, separately for observed (i.e., based on vegetation inventory data) and RS predicted (i.e., based on random forest modelling) gradients. These were plotted in two-dimensional space to show development of the vegetation, and to see if predicted changes were consistent with observed ones (Fig. 3). We conducted all statistical analyses with R version 4.2.1 using packages *vegan* (Oksanen et al., 2022), *randomForest* (Liaw and Wiener, 2022), and *VSURF* (Genuer et al., 2015).

3. Results

3.1. Peatland type-specific variable importance

The most important variables based on VSURF differed between peatland types (Fig. 4). For spruce mire forests, the most important variables were early summer NDWI (NMDS1) and midsummer NIR (NMDS2). For pine mire forests, the most important variables included midsummer red (NMDS1) and midsummer NIR (NMDS2). For open mires, the most important variables were partly the same as for pine mire forests. Midsummer red was the most important for NMDS1 and two vegetation indices (early summer SAVI, TCGreenness) were the two most important variables before midsummer NIR for NMDS2. Importantly, variables from both early and midsummer were found to be important for all peatland types and some variables, such as midsummer NIR and red, were consistently among the most important variables in all peatland types. The number of chosen variables was the highest for open mires (NMDS1 = 10; NMDS2 = 9), followed by pine (NMDS1 = 5; NMDS2 = 10) and spruce mire forests (NMDS1 = 4; NMDS2 = 5).

3.2. Peatland type-specific modelling performance

The constructed random forest regression models could predict floristic gradients (i.e., NMDS axes) with reasonable accuracy (%var explained = 28.62–69.44, nRMSE = 11.15–18.38 %; Table 3, Fig. 5). However, performance varied across peatland types. The highest overall performance was for open mires and the lowest for spruce mire forests.

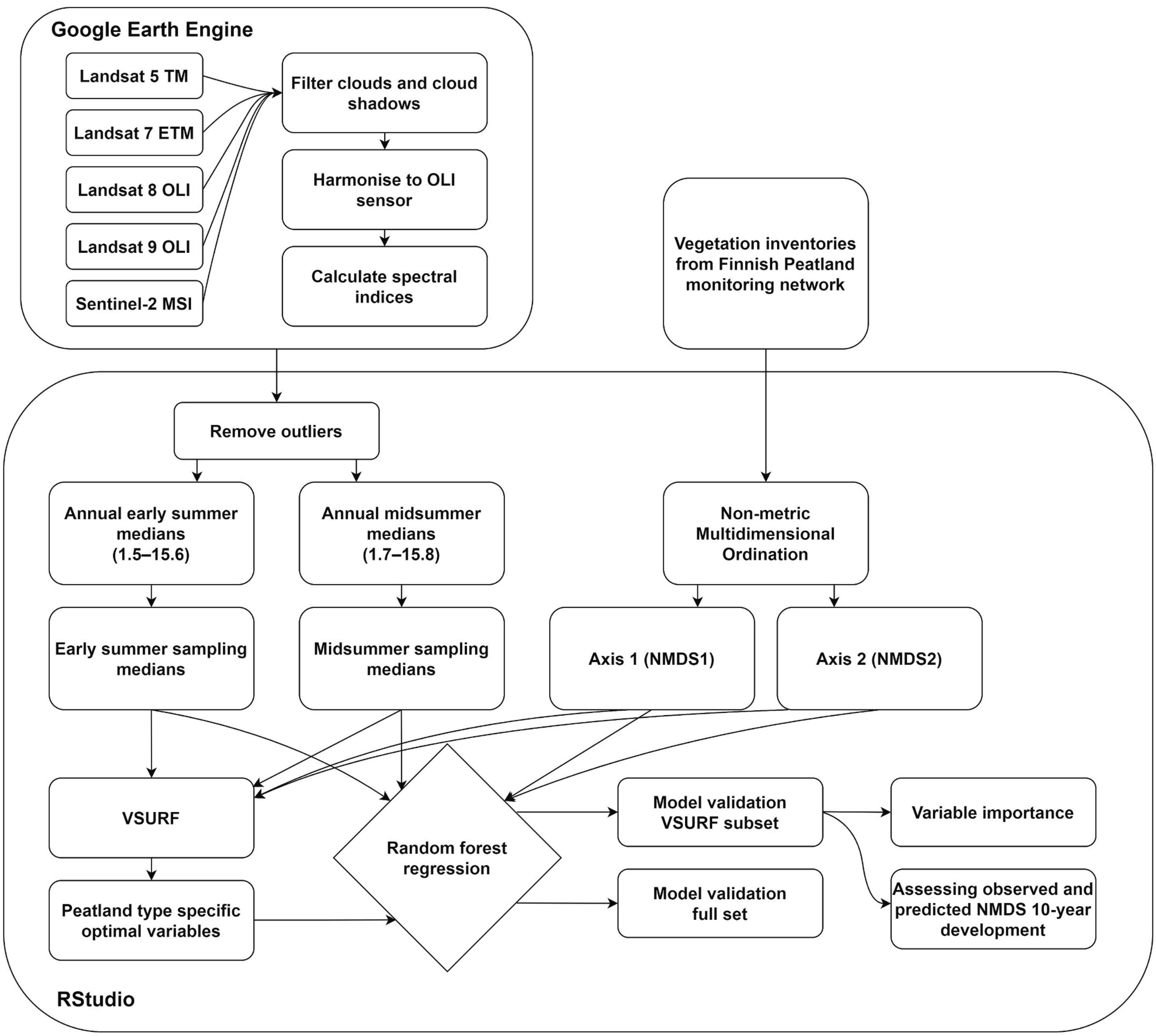

Fig. 3. Methodological flow chart. Spectral indices are listed in Table 1.

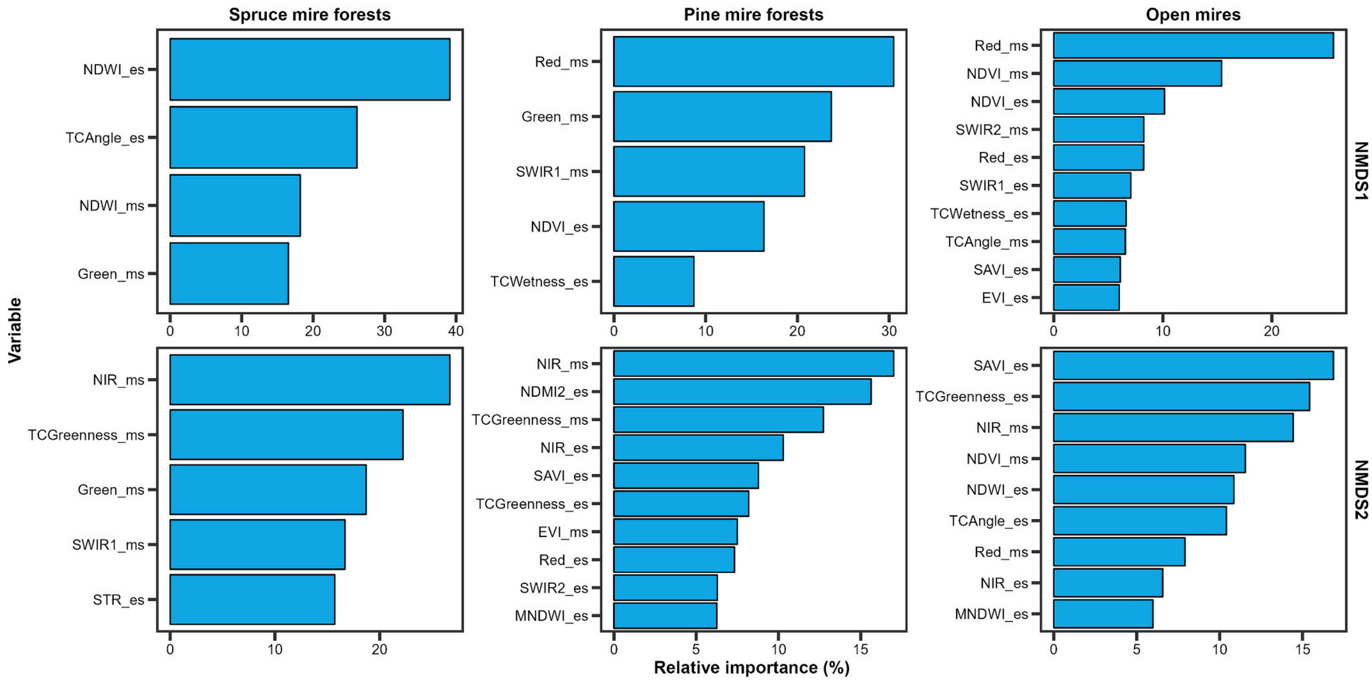

Fig. 4. Mean relative variable importance over 100 model fits for NMDS axes of spruce mire forests, pine mire forests and open mires. Abbreviations are explained in Table 1 and suffixes "_es" and "_ms" refer to early summer and midsummer, respectively. The models for calculating variable importance were run with the variables that were chosen after the VSURF prediction step.

Table 3
Mean percentage of variance explained (%var) and normalised root mean square error (nRMSE) of 100 fitted models for both axes. Full set refers to models constructed before variable selection and subset refers to models constructed with the variables selected by VSURF algorithm.

Type	Axis	%var full set	%var subset	nRMSE (%) full set	nRMSE (%) subset
Spruce mire forests	NMDS1	25.38	28.62	18.33	17.99
Spruce mire forests	NMDS2	28.37	36.27	19.48	18.38
Pine mire forests	NMDS1	51.59	52.86	18.23	17.99
Pine mire forests	NMDS2	30.02	33.10	17.19	16.81
Open mires	NMDS1	69.02	69.44	11.23	11.15
Open mires	NMDS2	34.10	37.26	17.11	16.70

Additionally, in open mires and pine mire forests, NMDS1 predictions had remarkably higher accuracy compared to NMDS2, but in spruce mire forests, both axes were predicted with a similar, quite low accuracy. Finally, variable selection improved the model performance in every NMDS axis.

3.3. *Observed and predicted temporal changes in floristic gradients*

The average of peatland type and treatment specific NMDS-axes demonstrated that the overall temporal behaviour was rather similar between the observed and RS predicted axes in pine mire forests and open mires, especially in restoration treatment (Fig. 6). However, in spruce mire forests, there was opposite restoration development in the RS predicted gradients compared to the observed ones. Additionally, the impact of restoration was mostly observed in NMDS1 for open mires while in pine mire and spruce mire forests, the impact was more apparent in NMDS2.

4. Discussion

4.1. *Importance of peatland type-specific remote sensing variables*

Our results indicate that vegetation in different peatland types, namely boreal spruce mire forests, pine mire forests and open mires, should be monitored with different satellite-based optical variables (Fig. 4). This is in line with previous studies (e.g. Räsänen et al., 2020; Steenvoorden et al., 2023) which have shown the differences in the importance of RS variables in predicting vegetation in different peatlands. However, our result is based on larger and more heterogeneous set of peatland sites than the previous studies, which makes our results more generalizable. Differences in important variables are probably caused by divergent vegetation composition in the different peatland types. Moreover, in densely treed spruce mire forests, satellites are mostly observing tree cover and shadows, while in open mires, ground vegetation is mostly observed. In pine mire forests, the RS signature is composed of trees, shadows and ground vegetation. Additionally, in hydrological monitoring of peatlands, the importance of variables and functionality of one variable differ between the sites and peatland types (Räsänen et al., 2022; Burdun et al., 2020, 2023) which further highlights the site and type specificity in RS studies.

Interestingly, our results suggest that SWIR bands are not important for predicting changes in vegetation patterns even though they have played a key role in monitoring peatland surface moisture and water table (Burdun et al., 2020; Räsänen et al., 2022; Burdun et al., 2023; Jussila et al., 2023; Isoaho et al., 2024). In our results, NIR band was important in every peatland type, which is in line with earlier studies depicting peatland vegetation and land cover (Middleton et al., 2012; Harris et al., 2015; Räsänen et al., 2020; Kolari et al., 2022; Steenvoorden and Limpens, 2023). NIR's ability to separate e.g. different *Sphagnum* species (Salko et al., 2023) might be one of the reasons behind

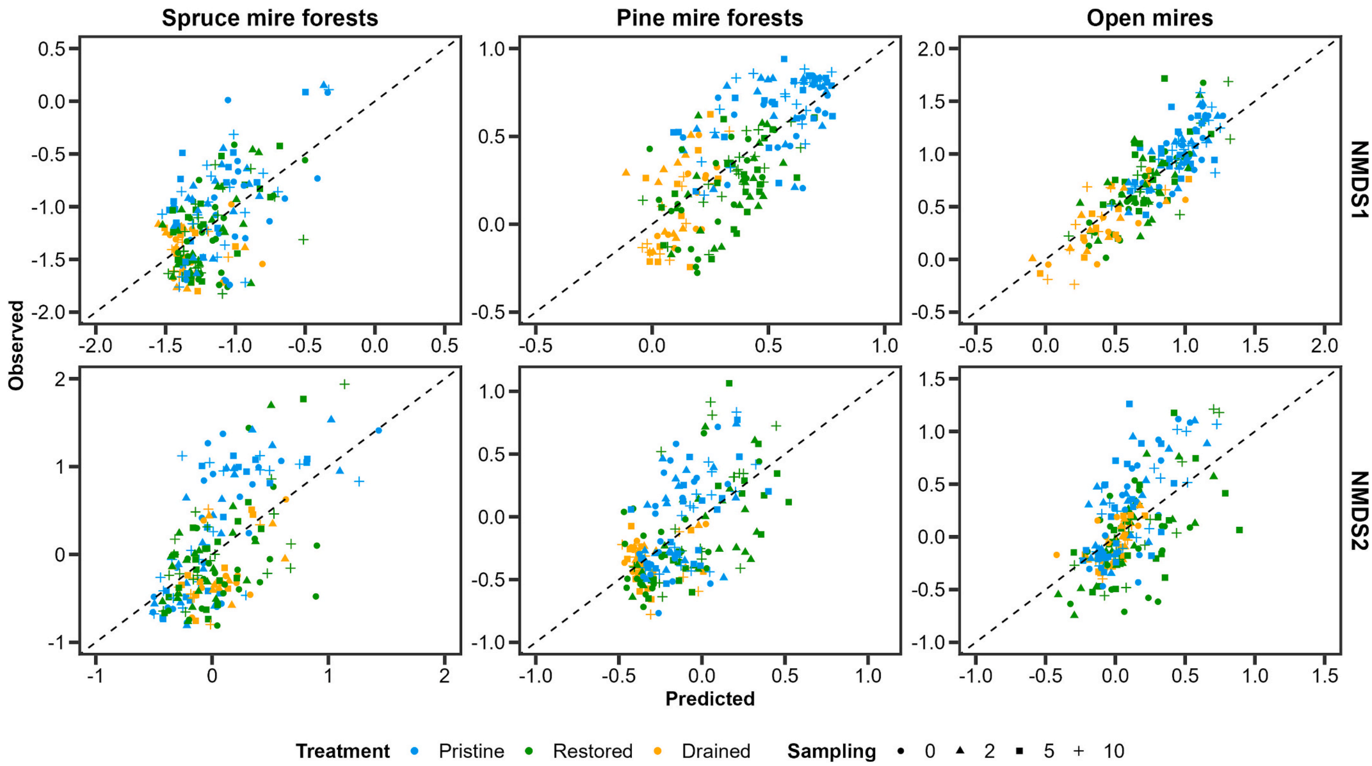

Fig. 5. Scatterplots between predicted (mean over 100 fits) and observed NMDS axes values, dashed line indicates 1:1 line.

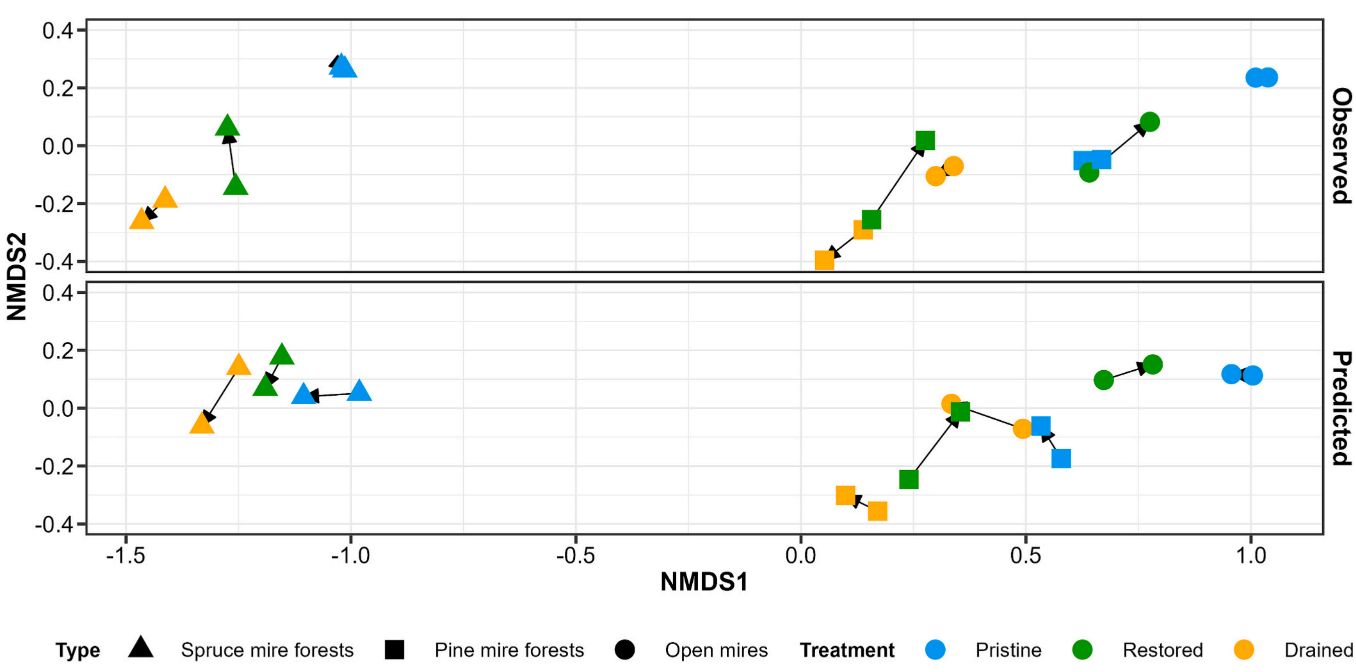

Fig. 6. Two-dimensional plot of observed and RS predicted floristic gradients with NMDS1 in x-axis and NMDS2 in y-axis. Points indicate average NMDS-values of peatland type and treatment over 0- and 10-year samplings. Arrow start from sample 0 and end in sample 10 showing the average development of the gradients over time. Observed NMDS development is very similar to Elo et al. (2024b) who used model-based ordination for a similar analysis with the same field data.

its importance. Furthermore, the importance of red band in peatland wetness prediction has been lately emphasized (Kolari et al., 2022; Isoaho et al., 2023). In our analysis, it is an important variable for predicting the wetness-related NMDS1 axis in pine mire forests and open mires (Figs. S1, S2). Nevertheless, there seems to be no one-size-fits-all solution but on average NIR and red band seemed to be rather important across the peatland types and floristic gradients.

As the most important variables include both early and midsummer observations, our results highlight the importance of multitemporal RS data that covers phenological and seasonal variation within the sites (e.g. Dudley et al., 2015; Halabisky et al., 2018; Räsänen et al., 2020). Early summer imagery shows the situation during spring floods and emerging vegetation (Räsänen et al., 2020) while midsummer imagery represents the vegetation phenological peak (Juutinen et al., 2017; Pang et al., 2023). The importance of multitemporal approach was also a key finding of recent study (Christiani et al., 2024) which successfully used early and midsummer time windows identical to ours for detecting peatland greenhouse gas sinks and sources of entire Finland with satellite imagery.

Additional RS and environmental datasets could further improve the floristic gradient predictions in the future studies. For instance, peatland vegetation predictions can be improved with high-resolution topographical data (Beyer et al., 2019; Harris and Baird, 2019; Räsänen et al., 2020; Korpela et al., 2020; Kaneko et al., 2024) or radar satellite imagery (Wijaya et al., 2010; Merchant et al., 2017; Khakim et al., 2020). In addition to RS variables, also other field-observation based variables, such as water table, can be used for explaining the floristic gradients (Pellerin et al., 2009; Maanavilja et al., 2014). The main challenge with the multisource approach lies in data availability. In our study, some sites have been monitored since 2007 and only optical satellite data is consistently available for the whole monitoring period. Topographic datasets are available only for specific time points and not consistently for pre- and post-restoration situations while radar imagery such as Sentinel-1 or ENVISAT offer limited temporal coverage of our monitoring period. Moreover, hydrological monitoring of the peatland monitoring network has been conducted only at a subset of sites (Räsänen et al., 2022).

4.2. Monitoring changes in peatland vegetation with remote sensing

Our results show that temporal changes in peatland vegetation can be monitored with optical satellite imagery. We have demonstrated that floristic gradients, which reflect community-level vegetation patterns and which are in our case quantified with NMDS axes, are predictable with optical satellite imagery in pine mire forests and open mires but not as validly in densely treed spruce mire forests. Therefore, in-line with the previous studies (Räsänen et al., 2022; Pang et al., 2023; Burdun et al., 2023), high tree cover seems to be an insurmountable obstacle for optical sensors. In sites where the ground vegetation is mostly hidden under tree canopy in coarser spatial resolution data, fine resolution sensor data could be tested in the future studies.

While long-term changes in microforms and habitat types have been previously monitored with RS techniques (Steenvoorden et al., 2022; Kolari et al., 2022), to the best of our knowledge, our results provide the first more frequent link between post-restoration vegetation changes and RS data in boreal peatlands. Previous studies have mostly focused on e.g. changes in peatlands' hydrological properties with optical data (Räsänen et al., 2022; Burdun et al., 2023; Isoaho et al., 2024) or on the spectral properties of restored and pristine sites (Ball et al., 2023). While hydrological changes can be drastic and quick (Menberu et al., 2016, 2017, 2018), changes in vegetation are slower (Elo et al., 2024b). This layout is difficult because drastic hydrological changes can be seen with RS data (Isoaho et al., 2024), even if changes in vegetation composition have presumably not occurred. Similarly, changes in spectral information are caused by tree cutting which could explain changes in restored treatments of pine mire forests and open mires. This raises the question of how much of the predicted change is actually due to changes in vegetation and how much is due to the other factors such as increased wetness and change in tree cover.

We used 10 1 m^2 vegetation plots for constructing training and validation data at each site. The plots were located within 15 m radius circular area from which we extracted satellite data. In a way, each site in our data resembles plots in the previous studies that have utilised higher spatial resolution RS data for one or few sites (Harris et al., 2015; Räsänen et al., 2020). We acknowledge that the 10 m^2 describes only around 1.5 % of the 15 m radius area causing a possible spatial mismatch that can affect the modelling performance. Because peatlands are spatially heterogenous (Räsänen and Virtanen, 2019; Steenvoorden and Limpens, 2023), it is possible that the vegetation sample does not describe the area fully. Additionally, particularly spruce mire forests have a high variation in species composition between plots of a single site and between the sites (Elo et al., 2024a, 2024b). This furthermore challenges our approach in spruce mire forests as NMDS may not be able to capture the within-site heterogeneity which hampers our ability to model them with satellite imagery.

One of the restoration targets is to recover target species (Haapalehto et al., 2011) which often are used as indicators of restoration success (Kyrkjeeide et al., 2024). However, species-level predictions in heterogenous areas with environmental or RS data are very difficult to implement (e.g. Maanavilja et al., 2014; Saarimaa et al., 2019; Simpson et al., 2024). Bayesian joint species distribution modelling (Ovaskainen et al., 2017) provides a potential solution to find relationships between individual species and environmental variables derived e.g. from RS data (e.g. Palmroos et al., 2023). Therefore, merging optical and radar RS variables, as well as other relevant environmental variables with vegetation data and conducting Bayesian modelling could be a future research avenue.

Vegetation communities in the Finnish peatland monitoring network sites have not fully recovered in 10 years (Elo et al., 2024b), which can also be seen with our RS-based approach (Fig. 6). Additionally there is a large variation in restoration effect (Elo et al., 2024b), but on average, a shift towards pristine-like vegetation has been achieved. We emphasize the need for the longer field monitoring while recognising that RS has potential to complement the field work. Future work should develop indicators for peatland restoration that are ecologically meaningful and detectable with RS.

Also other types of northern peatlands should be included into restoration monitoring schemes. These include e.g. rich fens, treeless eutrophic peatlands with unique vegetation, and flark fens, wet and treeless boreal peatlands with wet flarks altering with drier strings. Importantly, the highest areal need for peatland restoration in Finland is in large aapa mire complexes (Räsänen et al., 2023), and flark fens within the northern aapa mires are in transition from fens to bogs (Sallinen et al., 2019; Granlund et al., 2022; Kolari et al., 2022; Kolari and Tahvanainen, 2023). To conduct large-scale monitoring of the flark fen vegetation changes, there is a need to develop RS-based monitoring methods but also field-based calibration data is needed. Nevertheless, the developed approach could also be tested in sites lacking field-based monitoring. As different peatland types should be modelled with different RS variables (Fig. 4) and as the approach functions the best in peatlands with few or no trees, the approach requires existing knowledge about the peatland type for which there is geospatial information available for several countries (e.g. Minasny et al., 2023; Pontone et al., 2024). Additionally, visual interpretation of high-resolution satellite imagery or aerial imagery also enables definition of coarse level identification of peatland types when needed.

4.3. Implications for management

Our study suggest that vegetation of restored and pristine sparsely treed boreal peatlands can be monitored with optical satellite imagery, particularly by utilising spectral regions of red and NIR reflectance. However, there is a high variability between types in the modelling performance and in the variables that are sensitive to vegetation changes. Therefore, comprehensive peatland type or even site-specific field inventories are required when RS is used for predicting detailed changes in peatland vegetation. In other words, RS can be used to supplement and upscale field inventory-based observations of peatland plant community change. While we did not explore possibilities for detecting spatial patterns of vegetation, the floristic gradients can be spatially predicted if there is spatially comprehensive field inventory based training data available (see e.g. Harris et al., 2015). Spatial assessments using RS datasets are important because the spatial impacts on restoration are not uniform, as shown in relation to the hydrological impacts (Isoaho et al., 2024) and as field inventory data cover only a small proportion of the peatland sites under interest. Finally, current monitoring schemes should be continued to further capture the longer-term restoration impacts because currently, the sites have not fully returned to their pristine-like state.

5. Conclusion

We demonstrated that optical satellite imagery can be used for large-scale monitoring of floristic gradients and post-restoration vegetation changes in boreal peatlands. The most important explanatory RS variables consist of NIR and red band captured during early and midsummer periods. However, the most important RS variable combinations differ between peatland types. Therefore, peatland-type specific regression models are necessary for effectively monitoring the changes in peatland vegetation. Our results also show that vegetation changes in open mires and sparsely treed pine mire forests can be modelled with reasonable accuracy, whereas the explanatory capacity in densely treed spruce mire forests is lower. Future work could explore the use of RS data to monitor species-level changes and develop RS-based ecological indicators for peatland restoration monitoring. Overall, we suggest that optical satellite imagery can serve as a proxy for assessing the vegetation response to peatland restoration in peatlands with little or no trees.

CRediT authorship contribution statement

Aleksi Isoaho: Writing – original draft, Validation, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Merja Elo:** Writing – review & editing, Investigation, Funding acquisition, Data curation. **Hannu Marttila:** Writing – review & editing, Supervision, Funding acquisition. **Parvez Rana:** Writing – review & editing. **Anssi Lensu:** Writing – review & editing. **Aleksi Räsänen:** Writing – review & editing, Supervision, Project administration, Investigation, Funding acquisition, Conceptualization.

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.scitotenv.2024.177697.

Data availability

Data will be made available on request.

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