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Roadmap for genererating a soil map for Norwegian pristine mires

Hanna Silvennoinen, Zander Venter, Jenny Hansen, Marte Fandrem, Linn Marie Lunde, Anders Lyngstad, Magni Olsen Kyrkjeeide & Willeke A'Campo

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Mire landscape at Prestøyan, Stråsjøen Nature Reserve, Trøndelag
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Abstract

Silvennoinen, H., Venter, Z., Hansen, J., Fandrem, M., Lunde, L.M., Lyngstad, A., Kyrkjeeide, M.O., A'Campo, W. & Nilsen, E. 2023. Roadmap for generating a soil map for Norwegian pristine mires. NINA Report 2374. Norwegian Institute for Nature Research.

Under the umbrella of larger project 'Økologik tilstand', we created a roadmap for mapping soil biogeochemistry of Norwegian mires. Mapping soil characteristics, especially carbon and nitrogen stocks as well as their other chemical parameters, as well as physical and biological variables is important to better understand the consequences of various planned disturbances as well as their magnitude.

We searched for the availability of existing Norwegian contemporary and historical data to characterize future data requirements and to test predictive models applying remote sensing tools. To the date, only two datasets are available: a small limited contemporary data set published in Kyrkjeeide et al. (2023) and a large historical dataset collected by 'Myrselskapet' (Hovde 1971) and published and stored by NIBIO.

We digitalized and georeferenced this historical dataset, which is now published in Living Norway (Silvennoinen et al. 2023). The consists of various types of peatlands including drained and pristine and used selected parts of it to test the predictive models for mapping carbon and nitrogen densities. This was done as a pilot project to explore the potential for remote sensing and spatial modelling to monitor Norwegian mires. Our pilot study revealed that although we could map carbon and nitrogen densities, the models were attributed with large uncertainties. The models explained between 22 and 24% of the variance in carbon and nitrogen densities. This highlights the need for gathering contemporary in-situ field data for training and ground-truthing remote sensing models before they can be used for developing national soil maps for mires. The limited amount of 'Myrselskapet' data which is spatially biased (ie. concentrated in selected areas in Norway) combined with data age (between 61 and 85 years old) makes spatial modelling of mire geochemistry challenging. The dataset is also limited in the amount of data for critical variables, namely peat depth, in order to compute carbon and nitrogen stocks reliably.

Ongoing national soil monitoring programs concentrate on agricultural (JORVAAK - program) and forest soils ('Overvåking av jordkarbon i skog og beitemark') but fail to cover pristine mires. To generate a soil map for Norwegian mires, we emphasize the need for contemporary national data for ground-truthing remote sensing modelling methods. At this end, we recommend a one-time intensive sampling campaign (carbon, nitrogen and basic soil physical parameters with vertical and horizontal distribution along with peat depth measurements) for main mire types in Norway to generate a database that can be used to calibrate results from less intensive campaigns with larger geographic coverage. The generated data should be maintained in open access databases.

Estimated costs to generate a national soil map for peatlands are following:

1. Intensive data collection from selected mires to calculate carbon stocks
2. Extensive collection of peat depth data with large national coverage
3. Modelling the soil map

Costs related to point 1 are 1 450 000 kr for sampling of selected 30 mires. These costs include personnel and analysis costs but exclude travel costs. Inclusion of nitrogen analysis will increase the cost estimate by 500 000 kr.

We also recommend that soil depth measurements are included in ongoing soil monitoring programs on peatlands, which have broad national coverage (e.g., ANO). Costs related to point 2. are 75 000 kr per year (coordination, planning and data-analysis), and added field sampling costs of 15 000 - 30 000 kr (without travel costs) per ANO – location. Price per ANO-location varies depending on size and depth of mires at the location. Adding soil sampling (for better recording of carbon stocks) will increase prices per ANO- location by an estimated 10 000 kr.

Costs related to point 3. remote sense modelling of soil carbon content in 3-5 years are estimated to be 800 000 kr – 1 200 000 kr, assuming that data collection presented in points 1 and 2 are carried out.

Current methodology for measuring peat depth (the most critical parameter to quantify soil carbon stocks) is laborious and time consuming. Various methods including landscape modelling and remote sensing are being tested and developed internationally. Building up competence and incorporating such techniques in Norway would significantly expedite developing a comprehensive map for soil carbon stocks in Norwegian mires.

Sammendrag

Silvennoinen, H., Venter, Z., Hansen, J., Fandrem, M., Lunde, L.M., Lyngstad, A., Kyrkjeeide, M.O., A'Campo, W. & Nilsen, E. 2023. Roadmap for generating a soil map for Norwegian pristine mires. NINA Report 2374. Norwegian Institute for Nature Research.

Kartlegging av jordegenskaper er viktig for å bedre forstå konsekvensene av menneskeskapte forstyrrelser på jordsmonnet og omfanget av disse. I tilknytning til dette prosjektet har vi laget et forslag til veikart for "jordsmonnskart over norske myrer". Forslaget tar utgangspunkt i en pilot, - et modelleringsprosjekt der vi har brukt myrdata som tidligere er samlet inn. I denne piloten har vi testet metoder og hvilke databehov som må på plass for å beregne lagre av karbon og nitrogen i norske myrer. Metoden som ble testet er en kombinasjon av fjernmåling og romlige modellering ved bruk at maskinlæring.

I piloten undersøkte vi nåværende og historiske data med relevans for piloten der vi skulle teste prediktive modeller ved hjelp av fjernmålingsverktøy kombinert med feltdata for å estimere karbon og nitrogenlagre i myr. Vi identifiserte to datasett som var tilgjengelig for piloten: et lite, begrenset datasett samlet inn i nær nåtid publisert i Kyrkjeeide et al. 2023 og et stort historisk datasett samlet inn av Det norske Myrselskap (Hovde 1971) og publisert som pdf-er av NIBIO. Dette historiske datasettet fra 1900-tallet måtte digitaliseres før vi kunne benytte det i piloten. Datasettet er nå publisert i Living-Norway (Silvennoinen et al. 2023). Datasettet bestod av ulike typer torvmark, inkludert både drenert og urørt torvmark. Vi brukte utvalgte deler av datasettet som bakkesannheter til å teste fjernmålingsmodellene. Vi vurderte dette som en mulig og effektiv tilnærming for en framtidig utforming av jordsmonnskart karbon- og nitrogenlagre i norske myrer i Norge.

Pilotstudien viser at det er mulig å lage jordsmonnskart for myr der både karbon og nitrogenlagre er beregnet. Resultatet av modelleringen ga en viss usikkerhet og modellene forklarte mellom 22 og 24 % av variasjonen i karbon- og nitrogenlageret per arealenhet. Pilotstudien viser således at det er behov for å samle inn nye data fra nærmere vår tid og med en bedre romlig representativitet for videre modelleringsarbeid. Få og til dels gamle feltdata fra et begrenset område i Norge ga betydelige begrensninger for framstilling av jordsmonnkart i piloten. Nødvendige og kritiske data for framtidig modellering er særlig torvdybde. Torvdybde er nødvendig for å kunne beregne karbon- og nitrogenlagre på en pålitelig måte.

Nasjonale jordsmonnsovervåkingsprogram for åpen myr er for tiden ikke dekket av noen av de pågående jordsmonnsovervåkingsprogrammene. Framover er det planlagt innsamling av jordprøver i skog gjennom prosjektet 'Overvåking av jordkarbon i skog og beitemark' og i jordbruksjord gjennom det nyetablerte JORDVAAK-programmet. Vi anbefaler derfor at det for åpen myr etableres en intensiv innsamling av jordprøver på et utvalg lokaliteter som analyseres for karbon, nitrogen og grunnleggende jordfysiske parametere med vertikal og horisontal fordeling. Ved økt kunnskap om karbon og nitrogeninnhold i øverste jordlag får man kunnskap som er viktig for vegetasjonen. I tillegg til den intensive kartleggingen er det behov for torvdybdemålinger for de viktigste myrtypene. Sammen med kjennskap til vertikal fordeling av jordfysiske egenskaper gir dette grunnlag for å beregne totalt karboninnhold. Disse nye intensivt innsamlede dataene vil legge grunnlaget for å kalibrere innsamlinger av data fra mindre intensive kampanjer med større geografisk dekning. Alle data som samles inn anbefales å inkluderes i en åpen tilgjengelig database.

Kostnader for å få laget et nasjonalt jordsmonnskart er knyttet til:

1. Intensiv innsamling av data i et begrenset sett med myrer for beregning av karbon lagre
2. Ekstensiv innsamling av torvdybdemålinger
3. Modellering av jordsmonnskart

Kostnader for punkt 1) er beregnet til 1 450 000 kr. Dette inkluderer kostnader for intensiv prøvetaking av karbon i 30 myrer (inkludert personell og analysekostnader, eksklusiv reisekostnader). Hvis man også ønsker å inkludere nitrogenmålinger gir dette en tilleggskostnad på 500 000 kr.

Vi anbefaler at torvdybdemålingene legges inn pågående overvåkingsprogrammer med bred nasjonal dekning, der myr inngår (f.eks. ANO). Kostnader knyttet til punkt 2) er anslått til 75 000 kr per år (koordinering, planlegging og dataanalyse) og økt feltkostander på 15 000-30 000 kr per ANO- flate (uten reisekostnader da vi antar dette allerede er dekt). Prisene per lokalitet vil variere med størrelse og dybde på myrene på stedet. Å legge til jordprøvetaking (for bedre bestemmelse av karbonlager vil øke kostnadene per ANO-lokalitet med anslagsvis 10 000 kr.

Kostnader for punkt 3) modellering av karboninnhold i jord om 3-5 år basert på fjernmålingsmetodikken vi benyttet her, anslås til 800 000 -1 200 000 kr. Dette forutsetter at det er samlet inn tilstrekkelig med nye data i punkt 1) og 2).

Dagens metodikk for måling av torvdyp (den mest kritiske parameteren for å kvantifisere karbonlageret i jordsmonnet, er arbeidskrevende og tidkrevende. Ulike metoder, inkludert landskapsmodellering og fjernmåling, testes og utvikles nå internasjonalt for å utvikle en mer kostnadseffektiv måte å måle torvdybde på. Her kan data fra den intensive innsamlingen benyttes som bakkesannheter for de nye og innovative metodene. Ved å bygge opp kompetanse og ta i bruk slike teknikker i Norge, vil det være mulig å utvikle et omfattende kart over karbonlagrene i norske myrer.

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Contents

Foreword

'Roadmap for generating soil map for Norwegian pristine mires' was conducted as a sub-project under 'Indikatorer for økologisk tilstand i våtmark, semi-naturlig mark og naturlig åpne områder under skoggrensa" (Nybø et al. 2023). This independent report allows us to present more details than in the report from the main project.

Information on distribution, variability and vulnerability of soil carbon stocks is urgently needed in Norway for national and regional purposes. The scope of this project was to test the potential of remote sensing modelling for generating a national biogeochemistry map for mires with national coverage. The project further aimed at exploring the steps required for generating such a map.

The project was coordinated by Hanna Silvennoinen supported by Zander Venter. Zander Venter was responsible for digitalization of historical database as well as for supervising the work for the remote sensing modelling. Marte Fandrem searched and provided the data from 'Det Norske Myrselskap' and Linn Marie Lunde digitalized and georeferenced the dataset. Jenny Hansen and Willeke A'Campo carried out the modelling. Magni Olsen Kyrkjeeide, Anders Lyngstad and Marte Fandrem have participated in developing recommendations for sampling methodology for peat depth and carbon content. Erlend Nilsen organized and imported the data under Living Norway.

1.12.2023 Hanna Silvennoinen

1 Introduction

Norwegian pristine mires are under pressure, especially from various building projects for different infrastructures in local and national level. Increased awareness on vulnerability of these ecosystems and ecosystem services they provide (e.g., carbon stock, carbon sequestration, biodiversity, water retention), has led to prohibition of drainage for forestry and to initiatives to prohibit drainage for agriculture. Legislation, monitoring, and surveillance of various construction projects targeting pristine mires remains insufficient.

Therefore, there is an urgent need to better understand not only the distribution of pristine mires and mire types in Norway but also develop maps to elaborate the distribution of most important biogeochemical elements (carbon, nitrogen) in mires locally and nationally. Generating a biogeochemistry map for Norwegian pristine mires eventually using field data with remote sensing and machine learning is a method that can potentially be used to reach this goal. Such method, and remote sensing workflow when tested, can also be used for mapping carbon stocks and other biogeochemical variables in other ecosystem types such as grassland, forest or land use types such as croplands.

To spatially resolve (i.e., map) subsurface biogeochemical variables in mires, it's necessary to measure them directly with *in situ* samples, or develop models that factor in hydrological, biophysical, and topographic variables (Campbell et al. 2022). Hydrology, biophysical and topographic variables are the most important determinants of spatial variation in mire biogeochemistry. At the local scale this data can be obtained directly from the site using *in situ* sampling methods. However, for mapping and monitoring on a regional and global scale, a blend of in-situ data and remote sensing observations is essential. Although remote sensing introduces some uncertainty, it is vital for identifying spatial differences that onsite data alone can't provide. A review of 344 studies involving remote sensing of wetlands showed that the majority of work has focussed on mapping wetland types (Jararzadeh et al. 2022). The other application domains included analysing wetland phenological changes, surface vegetation types and biomass and wetland extent. Only 5% of the studies mapped wetland chemical content (mostly carbon). Nevertheless, the remote sensing maps of wetland biogeochemistry can often be produced in combination with maps of wetland types.

Carbon stock of Norwegian mires remains poorly characterized. Datasets with relatively broad national coverage for peatlands drained for both agriculture and forestry exist, whereas data from pristine mires are sparse constituting of only two datasets that can be used to compute carbon stocks are available. One of them is a historical data from 'Det Norske Myrselskap' collected as part of the inventory program of potential peatlands for development and use in the time period 1930-1980 (Hovde 1971; hereinafter referred to as 'Myrselskapet' data or dataset) The only public contemporary dataset for carbon stocks of pristine mires (Kyrkjeeide et al. 2023) is limited to few mires, that are classified by dominant mire types in Norway.

This work consisted of four main components: 1) acquiring, digitalizing and georeferencing the 'Myrselskapet' data (Hovde 1971), 2) importing the data to Living Norway database (Silvennoinen et al. 2023), 3) testing the potential of remote sensing tools combined to machine learning to expedite generation a national biogeochemistry map for Norway using the 'Myrselskapet' data and 4) creating a roadmap for a biogeochemistry map for Norwegian pristine mires.

In this report we concentrate primarily on carbon and nitrogen stocks as those data are available in the currently existing national data elaborated above. It is however important to keep in mind when evaluating the need for national soil monitoring programs and related costs, that other soil properties also play a critical role for ecosystems and their functioning. Peatlands are important in flood and fire control and function as buffer areas for leaching of nutrients. Importance of soil biodiversity is currently heavily emphasized at European level.

2 Pilot study using historical data

The primary objective of this pilot study was to derive biogeochemical attributes for a set of mires across Norway from a historical data set, 'Myrselskapet' to use as response variables in models containing remotely sensed predictor variables. Remote sensing offers a more affordable way to gather knowledge, allowing for broad, detailed data collection at consistent times. This method yields extensive and useful data sets, as long as they accurately reflect real-world conditions and include measured uncertainty. It also requires a robust data infrastructure and mapping solution for the final user. Internationally, many studies have shown the potential remote sensing has for mapping and classifying wetlands (Venter et al. 2021a). However, there is less research on how remote sensing can be used to map wetland biogeochemistry. Optical remote sensing of wetland physical and chemical content relies on using spectral responses of surface vegetation as a proxy for the sub-surface content. Alternatives to optical remote sensing are active radar sensors which have the ability to penetrate the surface vegetation and in some cases the top layer of soil. However, aerial and satellite remote sensing are not able to directly sense wetland soil content. Nevertheless, landscape variables such as terrain and surrounding land cover, climate, and satellite-derived spectral responses can all be used to model and predict wetland biogeochemistry in the same way it has been done for other ecosystems (e.g., Venter et al. 2021b).

In this pilot study, we used data gathered by 'Det norske myrselskap' to test the remote sensing of mire nitrogen and carbon density. We aimed to determine (1) which remote sensing variables might best predict biogeochemical attributes in mires across Norway, (2) how accurately machine learning models could predict mire biogeochemistry, and (3) what are the areas for improvement in terms of collecting better in-situ data in the future.

A secondary objective is to assess the value and challenges of working with a historic data set like the 'Myrselskapet' -dataset for future carbon modelling in Norway. The dataset is from the period 1940-1960 and has been stored as PDFs with NIBIO. We digitized these maps by defining polygons around each sampled mire, linking them to the biochemistry data. Although this is an important resource, the age of the data, spatial distribution, and method of digitizing can pose some challenges for future use of the dataset.

2.1 Methods

2.1.1 Study area

The study area (Figure 1) encompasses Norway, with records in five counties and 49 municipalities. Counties containing mires are: Innlandet, Møre og Romsdal, Nordland, Troms og Finnmark, Trøndelag, and Viken. Municipalities that have at least one mire are: Alstahaug, Andøy, Aremark, Aukra, Averøy, Brønnøy, Bø, Dønna, Elverum, Giske, Hadsel, Halden, Hamar, Hareid, Harstad, Herøy, Hustadvika, Indre Fosen, Kvæfjord, Leirfjord, Lurøy, Løten, Meløy, Molde, Namsos, Nærøysund, Osen, Ringsaker, Rosse, Rødøy, Smøla, Sortland, Steigen, Steinkjer, Sømna, Sør-Varanger, Trysil, Træna, Ulstein, Vardø, Vega, Vestnes, Vestvågøy, Vågan, Våler, Øksnes, Ørland, Åfjord, and Ålesund.

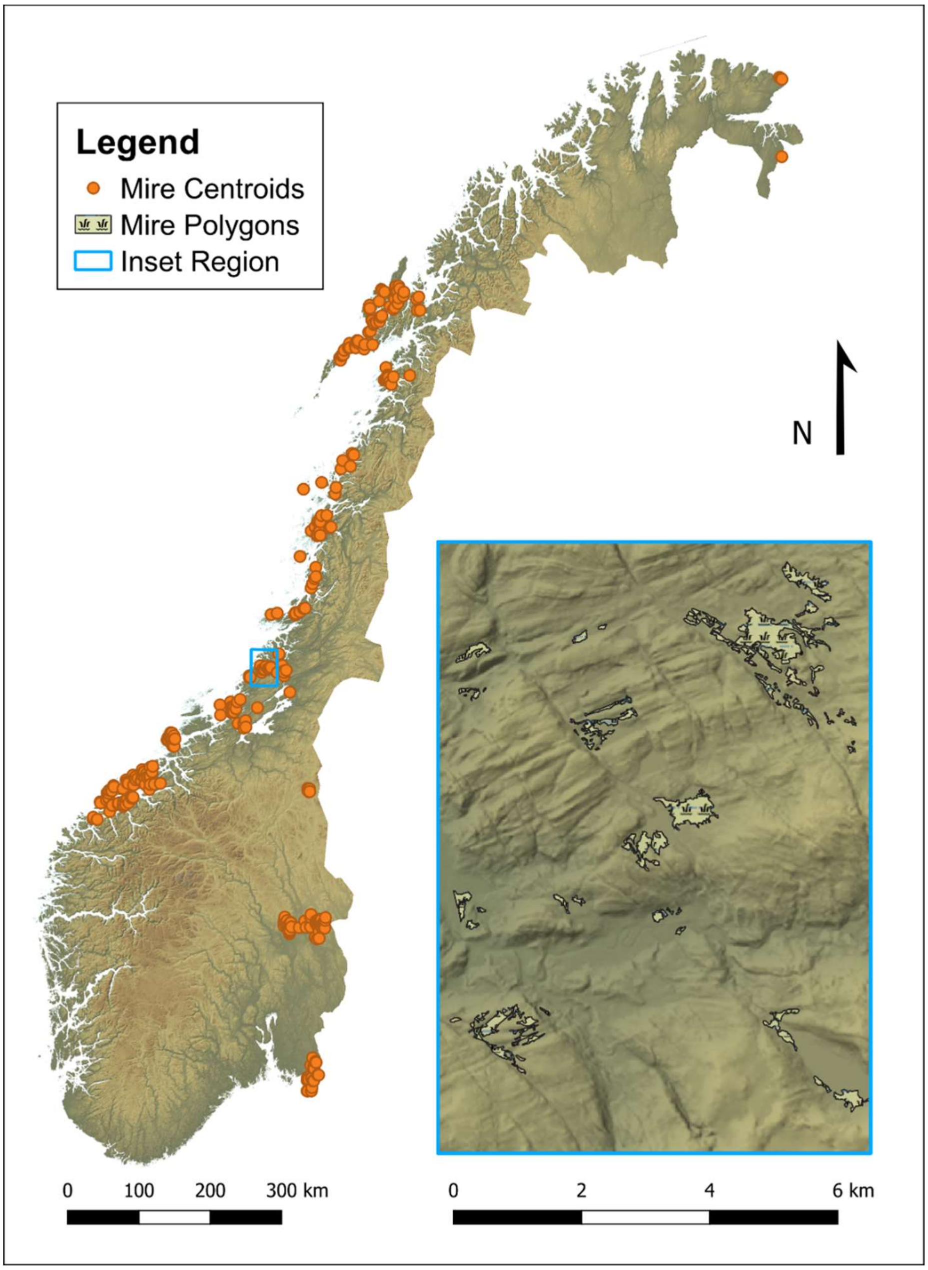

Figure 1. Map of Norway showing mire locations (centroids). Topographical variation in terrain around the mires can be seen in the region.

2.1.2 Data and mire polygons

The 'Det norske myrselskap' dataset was obtained from NIBIO in the form of PDF documents with tables of biogeochemistry measurements and associated hand-drawn maps. When consolidated, the dataset comprises various biogeochemical variables unevenly sampled from mires across Norway. We digitized 348 polygons from <source>, in manually outlining the hand-drawn mire polygons in QGIS using landscape features and orthophotos for reference. We then linked the polygons by name to the 'Myrselskapet' data. Specifically, we extracted values for ash percentage, bulk density, peat depth, and nitrogen content (measured in kg per dekar up to a 20 cm depth). To calculate the carbon stock per mire, we employed the formula:

Peat depth × Bulk density × (Ash percent ÷ 100) × 0.5

where ash percent was used as loss of ignition corresponding to the amount of soil organic matter. 0.5 is a conversion factor soil organic matter/soil organic carbon according to Pribyl (2010).

We divided the original nitrogen data by 1000 to obtain nitrogen stock in kilograms per square meter. The density distribution of carbon and nitrogen stocks are shown in Figure 1. We successfully matched 320 digitized polygons with corresponding biogeochemical variables (from time period 1930-1980) for use in our modeling procedure.

It is important to note that when we refer to “stocks” we are referring to C or N density per square meter of mire which is commonly referred to as “density”. To calculate actual C or N stock for a mire, the density would be multiplied by the area of the mire.

2.1.3 Remote sensing variables

We imported the 320 polygons into Google Earth Engine (GEE) as a feature collection and aggregated predictor variables over each polygon. Predictor variables are the terrain, climate and remote sensing variables used to extrapolate (ie. predict) mire nitrogen and carbon densities over space. Below is a list of remotely-sensed variables that were extracted for each mire polygon and used as predictor variables for the models.

Terrain variables were extracted from the Norwegian digital terrain model and digital surface model (https://hoydedata.no/LaserInnsyn2/) with 10 m resolution and are as follows: minimum elevation, mean elevation, maximum elevation, slope, aspect, and canopy height model (CHM).

Climate variables were extracted from the WordClim data set (Fick and Hijmans 2017) and are as follows: isothermality, annual mean precipitation, precipitation seasonality, precipitation of coldest quarter, precipitation of warmest quarter, precipitation of driest month, precipitation of driest quarter, precipitation of wettest month, precipitation of wettest quarter, annual mean temperature, temperature annual range, mean diurnal range, temperature seasonality, mean temperature of coldest quarter, min temperature of coldest month, mean temperature of warmest quarter, max temperature of warmest month, mean temperature of driest quarter, and mean temperature of wettest quarter.

Biological variables were extracted from the Sentinel 2 satellite imagery available on GEE. We term these “biological” because the spectral responses from mires are a god proxy for the surface vegetation structure and composition. The spectral data extracted include: median blue band reflectance, median green band reflectance, median red band reflectance, median R1 reflectance, median R2 reflectance, median R3 reflectance, median NIR reflectance, median SWIR1 reflectance, median SWIR2 reflectance, NBR standard deviation, spring NDVI, fall NDVI, summer NDVI, 5th percentile of NDVI, 25th percentile of NDVI, median NDVI (50th percentile), 75th percentile of NDVI, 95th percentile of NDVI, NDVI texture standard deviation, 5th percentile of NDSI, 25th percentile of NDSI, median NDSI (50th percentile), 75th percentile of NDSI, and 95th percentile of NDSI.

We also extracted synthetic aperture radar backscatter from the Sentinel 1 imagery on GEE. Radar responds to the vegetation structure and moisture content and can be given complementary information to optical data (Sentinel-2). The variables extracted included: median dual-polarization ascending orbit, median VH polarization ascending orbit, VH polarization standard deviation ascending orbit, median VV polarization ascending orbit, VV polarization standard deviation ascending orbit, median dual-polarization descending orbit, median VH polarization descending orbit, VH polarization standard deviation in descending orbit, median VV polarization in descending orbit, and VV polarization standard deviation in descending orbit.

Prior to use in models, predictor variables were checked for missing values, outliers, and collinearity. In every type of predictor (terrain, climate, and biological), several variables were highly collinear (ie. they were strongly correlated with one another). This partially informed our choice to use random forest regression, which is typically not affected by multicollinearity of predictor variables.

2.1.4 Statistical analysis

Due to the constraint of limited sample sizes (at most n = 294 for nitrogen stock), three separate models for each response variable (6 total training models – 2 response variables x 3 types of predictor variables) were constructed to prevent overfitting. These grouped models were fit for 1) terrain, 2) climate, and 3) biological variables. Prior to fitting models, we imputed missing values for the predictor variables.

For each model, the dataset was divided into training and testing sets, with 75% of the data used for training and 25% reserved for testing, through stratified (strata = response variable) random sampling. We created a dataset from bootstrap resampling to perform cross validation and fine-tune the hyperparameters of the Random Forest models. We used a grid of size = 50 to randomly try different combinations of the following hyperparameters: number of trees in the forest (trees), number of variables sampled at each split (mtry), and minimum number of data points in a node (min_n). Hyperparameters were tuned using the tune grid function from the ‘ranger’ (Wright and Ziegler 2017) package in R and performance metrics were used to select the best fitting model for each response variable.

We evaluated the importance of predictors for each group model to determine which variables would be retained for the final set of models. Post-training, a variable importance plot was generated using the ‘vip’ (Greenwell and Boehmke 2020) package to rank the importance of each predictor. We used importance values combined with collinearity to select the final variables. Variables were selected in order of the importance and could not have a relatedness coefficient greater than ±0.7 with any of the other predictors in the model.

We took the retained predictors from each grouped model and created a final model that contained all predictors from the terrain, climate, and biological groups that were found to be important. The procedure for fitting and assessing the final models was identical to that of the grouped models.

2.1.5 Model prediction/performance

In order to generate spatially-explicit predictive maps of carbon and nitrogen stock, we identified a subset of 2061 mires from the county of Møre og Romsdal. Mires were identified from the arealressurskart ‘AR5’ map produced by the Norwegian Institute for Bioeconomy (NIBIO 2021) and the subset obtained in QGIS. We then extracted the same terrain, climate, and biological variables in GEE over each of the polygons in the Møre og Romsdal subset. This data served as the ‘new data’ in the prediction function from which we obtain spatially-explicit predictions of carbon and nitrogen stocks. We used three metrics to determine model performance for each of the final models, root mean square error (RMSE), mean absolute error (MAE), and R-squared. We extracted RMSE and MAE values from the fitted model objects and compared those to a null model to determine the ‘improvement’ of the fitted model over the null. We used the R2 value to determine how well the predictors explain variation in the response variable data. The formulas for determining performance improvement are as follows:

Percentage Improvement in RMSE = ((RMSENULL - RMSERF) / RMSENULL) x 100
Percentage Improvement in MAE = ((MAENULL - MAERF) / MAENULL) x 100

2.2 Results

2.2.1 Descriptive

From the data gathered by 'Det norske myrselskapet', we obtained 139 observations for carbon stock and 294 observations for nitrogen stock. The distributions of these response variables are shown in Figure 2 and descriptive statistics are provided in Table 1. Most of the remote-sensed predictor variables were extracted over 320 mires, with some exceptions. The C:N ratios ranged from 15 to 70 which is within the range expected for Norway. However, the C density of mires in 'Myrselskapet' data averaged 7.4 kg/m² which is lower than expected (Bargmann et al. 2023 and references therein). From our experience digitizing the mires, we found that many of them were under anthropogenic pressures and were likely drained for forestry or agriculture in the past which has lowered their C densities. It is also possible that the 'Myrselskapet' dataset was biased to easily-accessible areas and that the more carbon-rich mires in remote locations were under-represented.

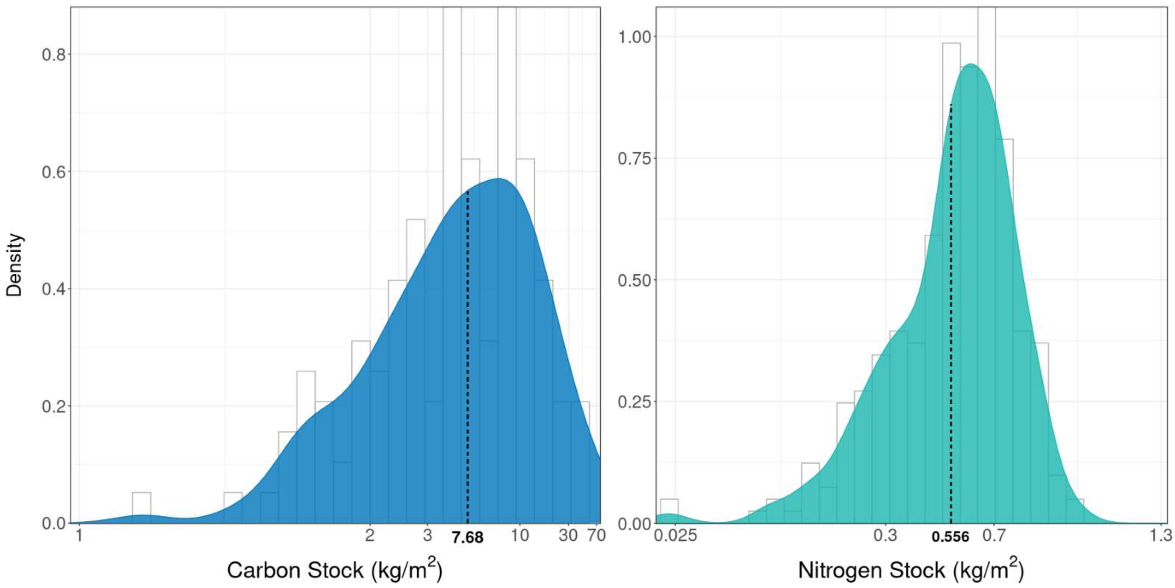

Figure 2. Side-by-side plots displaying the density distributions of carbon (left panel) and nitrogen (right panel) stock in kg/m². Both plots show log-transformed density distributions and histograms to improve interpretation. However, the x-axes are labeled with the original, untransformed scale. Dashed vertical lines represent mean values (carbon = 7.68 and nitrogen = 0.556)

Table 1. Summary statistics for response variables collected in 308 mires across Norway. Statistics include the number (N) of samples available, mean, standard deviation, minimum and maximum values recorded.

Variable	N	Mean	Std. Dev.	Min	Max
Carbon stock	153	7.44	10.02	0.69	70
Nitrogen stock	308	0.56	0.23	0.05	1.38

2.2.2. Importance of predictor variables

For both C and N stocks, climatic variables were most important predictors (Figure 3). This indicates that the largest variation in C and N are due to climatic gradients over Norway due to the large geographical spread of the 'Det norske myrselskap' data (Figure 1). Terrain variables like elevation and slope were also important predictors, emphasising the significance of topographic position which influences the hydrological formation of mires. Remote sensing variables were also important with radar variables from Sentinel-1 being more important for predicting C stock compared to N stock. In contrast, optical variables like NDVI were more important for predicting N stock compared to C stock.

Carbon stock - After running the grouped models, the following predictors were found as important and used in the final model for carbon stock: elevation, Canopy Height Model, precipitation in the wettest month, temperature seasonality, isothermality, median red band reflectance, 50th percentile NDVI, median SWIR2 reflectance, median NIR reflectance, median dual-polarization ascending, and median VH ascending (Figure 3).

Nitrogen stock- After running the grouped models, the following predictors were found as important and used in the final model for nitrogen stock: elevation, slope, temperature in the driest quarter, precipitation in the coldest quarter, precipitation seasonality, isothermality, 25th percentile NDVI, 95th percentile NDSI, and median red band reflectance (Figure 3).

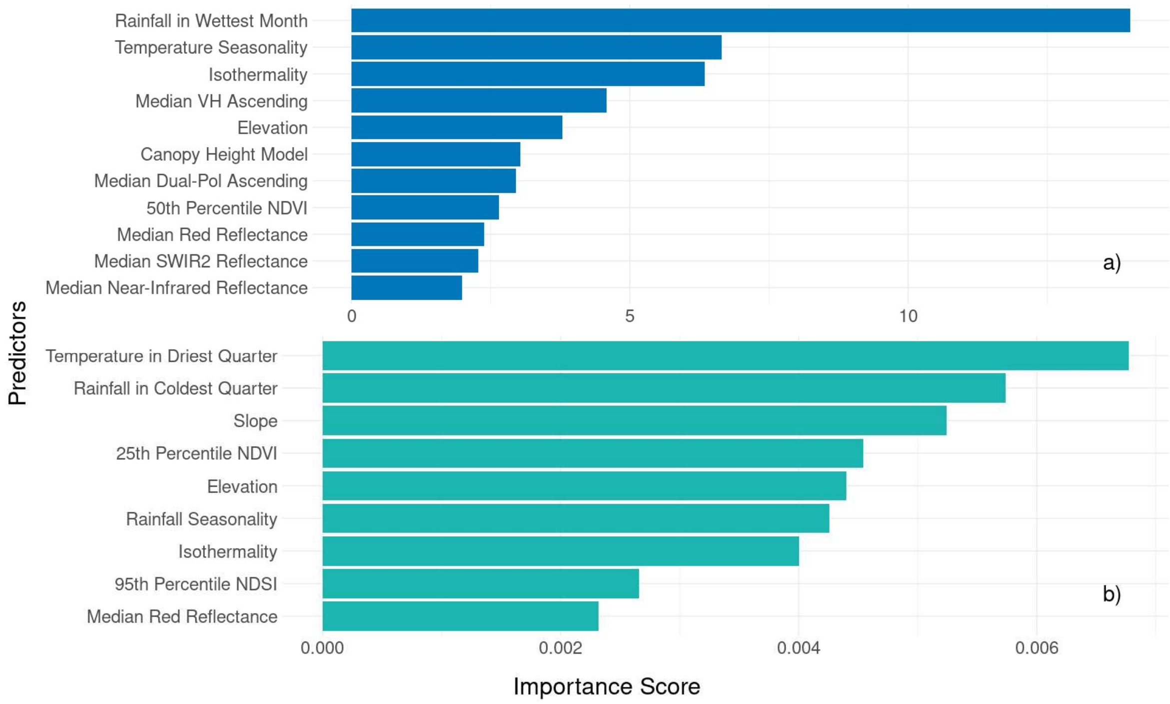

Figure 3. Predictor variables identified as 'important' following Random Forest modelling for a) carbon stock and b) nitrogen stock. Predictors are arranged in order from most to least important.

The fitted carbon stock model had an RMSE of 6.71 and an MAE of 5.19, compared to the null model's RMSE of 7.43 and MAE of 5.38. This shows a 9.68% improvement in RMSE and a 3.52% improvement in MAE over the null model. The R2 value for the fitted model was 0.235, which indicates that the fitted model explains approximately 23.5% of the variance in carbon stock.

For nitrogen stock, the fitted model had an RMSE of 0.212 and an MAE of 0.167, compared to the null model's RMSE of 0.237 and MAE of 0.185. This represents a 10.67% improvement in RMSE and a 9.84% improvement in MAE, indicating that the fitted model performs significantly better than the baseline null model. The R2 value of 0.217 suggests that the fitted model explains approximately 21.7% of the variance in nitrogen stock.

2.2.3 Predictive modelling

We identified 2061 mire polygons in Møre og Romsdal to use for spatially-explicit predictive mapping. After extracting the predictor variables from corresponding GEE scripts, they were compiled into a unified dataset by merging them on a common attribute. From the newly-generated predictors, we included only those that were identified as important from our fitted carbon and nitrogen stock models.

After applying the pre-trained Random Forest models to the dataset containing the new predictors, we generated new predictions for carbon and nitrogen stocks across the Møre og Romsdal mires, which we integrated back into our original spatial framework. These spatially explicit predictions were used to generate prediction maps for carbon stock (Figure 4) and nitrogen stock (Figure 5).

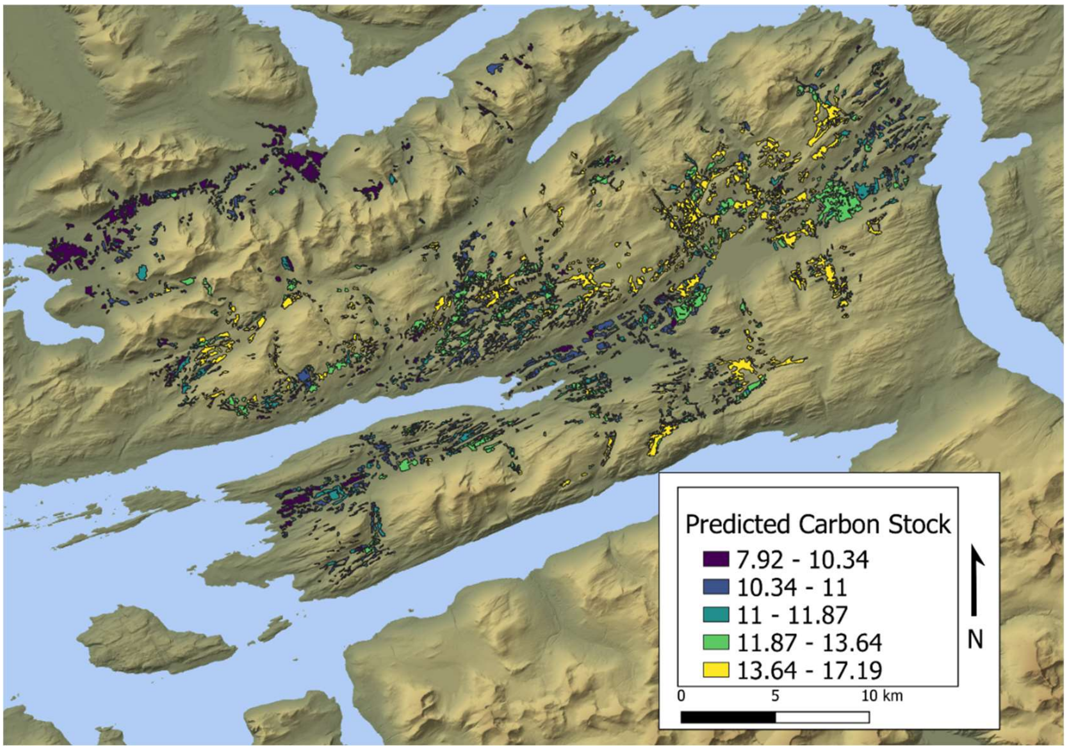

Figure 4. Prediction map of carbon stocks across 2061 mires in Møre og Romsdal county in Norway.

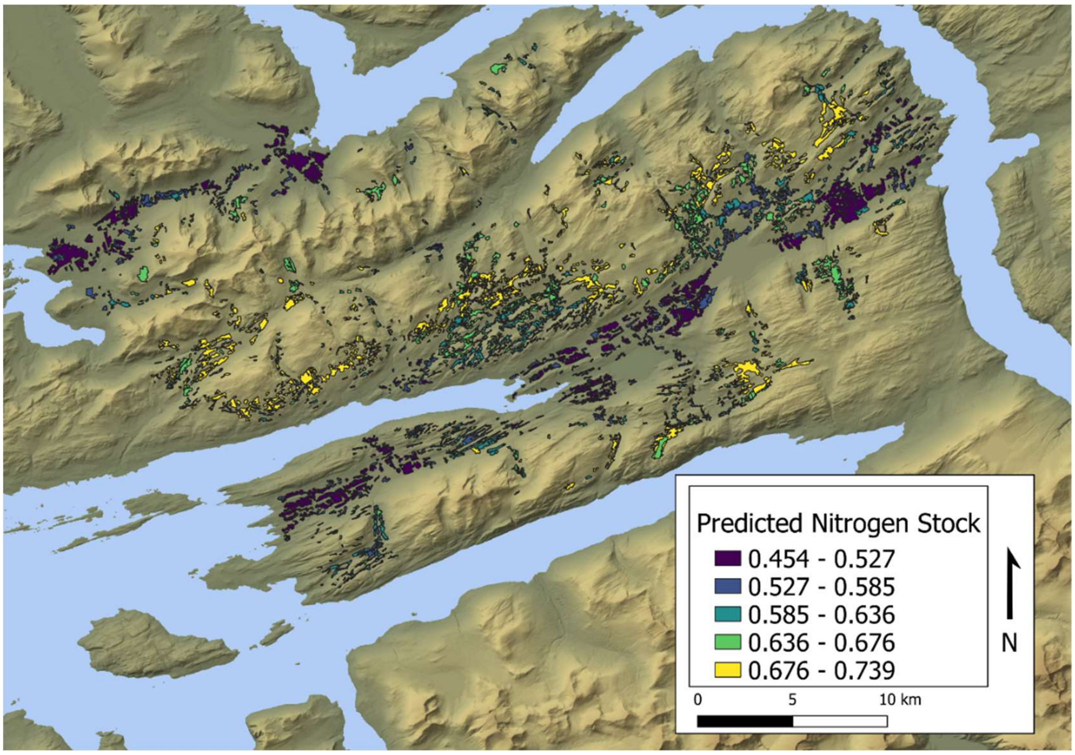

Figure 5. Prediction map of nitrogen stocks across 2061 mires in Møre og Romdsal county in Norway.

2.3 Conclusions of the pilot study

The pilot study using the 'Myrselskapet' data was useful to explore the possibility of mapping mire biogeochemistry using satellite remote sensing and machine learning. We found that climatic and edaphic variables were slightly more important than remote sensing data in explaining the spatial variation in C and N densities over Norway. Although we were able to create maps of C and N stock densities over a test area, the spatial models were uncertain. We were only able to explain between 22 and 24% of the variation in N and C densities, respectively. The model root mean square errors were large relative to the range of values in the 'Myrselskapet' dataset. For instance, the C density root mean square error was 6.67 kg/m2. In the example of Møre and Romsdal (Figure 5), this is nearly 50% of the range of predicted C density for this landscape (range between 8 and 17 kg/m2). This means that one could not distinguish mire C stocks in this landscape with high statistical confidence.

Several challenges and opportunities have arisen during our analysis:

1.Sample Limitation: Our data covers a limited number of mires, leaving substantial regions of Norway underrepresented. Therefore, our results are not generalizable to all mires in Norway. For instance, we suspect that the 'Myrselskapet' data was biased to disturbed mires with lower C stocks. It therefore remains to be seen how well spatial modelling can predict the full range of C and N content in pristine mires over Norway.

2. Data Age: The age gap between our historic and modern data ranges from 61 to 85 years. Changes in land use and climate during this period could reduce the accuracy of our predictions based on modern data. Ideally, the response variables and predictor variables in a spatial model should be from the same period to ensure most accurate results.

3. Limitations of remote sensing: The pilot study revealed the limitations to remote sensing and spatial modelling of mire biogeochemistry. Although the errors in the models could have been due to the temporal mismatch between 'Myrselskapet' data and predictor variables, there is a finite limitation to how well satellite- or airborne sensors can detect subterranean content. Aerial remote sensing will always have to rely on surface vegetation as a proxy for mire biogeochemistry and therefore always be an indirect measure with associated uncertainties. Nevertheless, the true potential for remote sensing and spatial modelling can only be quantified when we have an up-to-date and spatially representative field dataset of mire biogeochemistry to work with.

3 Recommendations for future monitoring

As concluded above, *in situ* measurements of carbon stocks are needed for ground-truthing predictive modelling with remote sensing tools, that may be used to generate a high-resolution map of carbon stocks with national coverage. Here, we make recommendations for the steps required to generate such map as time as cost-efficiently as possible.

3.1 Harmonizing sampling and monitoring methods

Currently, there is a large interest both at national and regional level to characterize different peatland areas to guide various construction projects. Multiple soil sampling programs are also ongoing and starting (See section 3.2 below). It is critical that methodologies, especially those used for quantifying soil carbon stocks, are harmonized and standardized per ecosystem in order to ensure quality of the quantification and to allow use of the data to build a national database for soil carbon spanning critical ecosystems (agricultural, forestry and mires). Municipalities are currently under pressure to define carbons stocks for decision-making regarding various infrastructure building. Using standardised methodologies per ecosystem in the various projects initiated by this need as well as open sharing of the resulting data for national mapping purposes would help building up databases to ground-truth national mapping efforts.

3.2 National peatland database

As a part of the GRAN-project (NFR grant 282327) NINA built a peatland database tailored mainly for quantifying soil carbon stocks (Kyrkjeeide et al. 2023). The data contains carbon stock variables for main mire types in Norway (bogs, poor fens, intermediate fens and rich fens). The physical and chemical variables contributing to peatland carbon stock vary depending on the type of the mire (various types spanning from ombrotrophic bogs to nutrient rich fens) but appear to be similar within mire types. The aim of the peatland database is to allow for retrieving values for parameters other than peat depth (e.g., bulk density, carbon content) for target areas, which will make monitoring carbon stocks less laborious and more cost-efficient on a national and regional levels (https://carbonviewer.nina.no). Further data collection is, however, needed to reduce the uncertainty of the parameter values within peatland types pertaining to the limited data currently available in the database.

We recommend carrying out a one-time sampling campaign covering 30 sites of dominant mire types located so that sampling with heavy gear is feasible. To cover vertical and horizontal variability, peat profiles of each mire should be sampled from five sampling points on a gradient spanning from mire edges to the centre. The peat profiles should be sampled from 0 – 250 cm (below vegetation) using corers tailored for peat sampling with 50 cm intervals resulting to up to 5 samples per profile and up to 25 samples per mire. As a minimum recommendation, bulk density, dry weight and loss of ingnition should be measured. Additional analysis for nitrogen would allow computing nitrogen stocks in addition to carbon stocks. In addition, peat depth should be measured every 20 m as specified in Kyrkjeeide et al. (2023) to report total carbon stocks for the sites.

Estimated costs for such sampling campaign sum up to 1450 – 1 750 KNOK, consisting of 300 KNOK for field sampling, 150 KNOK for planning, coordination, and data-analysis as well as 130 KNOK and 300 KNOK for analysis costs without and with analysis for nitrogen stocks, respectively. Travel costs and compensations are not included in this estimation, as specified site selection will significantly affect them.

3.3 National monitoring program for mires

Large scale soil monitoring programs prompted by EU-driven initiatives are starting and ongoing in Norway, namely JORDVAAK -program targeted for agricultural soils (JordVAAK -

Implementering av nasjonalt jordovervåkingsprogram på jordbruksjord - Nibio) and 'Overvåking av jordkarbon i skog og beitemark' (Overvåking av jordkarbon i skog og beitemark - Nibio) targeted to forests and meadows. To our knowledge, monitoring carbon stocks from pristine mires is not included in any of the ongoing or planned national programs.

Peat depth varies greatly between sites, depending on e.g. mire type and region. We recommend, as a minimum, to add peat depth measurements for locations, where mires appear, in the ongoing ANO- monitoring program (Arealrepresentativ naturovervåking (ANO) (nina.no)). This will improve the knowledge base for average peat depth in Norway and can be used for improved estimates and modelling of total carbon stocks in Norway. At this end, we recommend using a calibrated methodology where peat depth is measured every 20 m (Kyrkjeeide et al. 2023). Cost estimates for executing such measurement may vary greatly depending on the size and depth of mires at ANO-locations. In a recent case study, Lyngstad et al. (2023) followed this methodology, and found that it was possible to measure peat depth in 0.4 ha per day. The method requires two persons for efficient data collection. A coarse average estimate computed with 2-4 additional technical staff to carry out the field measurements (excluding travel costs and travel compensations) would increase the current costs of the ANO -programme by 15 KNOK per ANO-location and by an estimated 75 KNOK/year for planning, coordinating and data-analysis.

Additional soil sampling to generate more reliable estimates for soil carbon stocks is generally recommendable, and an absolute necessity if the above-described intensive field sampling for peatland database is not carried out. Standard methods using soil cores are not feasible for this purpose, due to logistical challenges pertaining to the ANO – program (remote areas, poor accessibility). We therefore recommend collecting five 10 x 10 cm soil samples from the top peat (0-50 cm below vegetation) using light sampling equipment along a gradient so that both the edges and the centre of the mire is included in the replication. Concentrating on simple soil variables (i.e. bulk density, dry weight and loss of ignition) renders the added costs reasonable, while generating sufficient data for estimating carbon stocks of the measured mires as well as providing data for remote sensing modelling for generating a national map of carbon stocks for mires (see below). Incorporating such light soil sampling would add to the costs per ANO site by 10 KNOK. This includes personnel costs but excludes travel costs and compensations.

While *in situ* field surveys are accurate, they are point-based samples with limited spatial coverage. For exploring municipal-level patterns, calculating ecosystem condition, and reporting to Eurostat on ecosystem services, we require wall-to-wall maps of soil biogeochemistry. Therefore, spatial modelling is useful and necessary for some use purposes. Another advantage is that wall-to-wall maps can be used to design and stratify future field surveys. The soil field data from JORDVAAK, 'Overvåking av jordkarbon i skog og beitemark' and (if implemented) an ANO soil program could serve as reference data for training satellite-based machine learning models to map soil biogeochemistry over the whole country. To be useful for satellite-based mapping, the survey data would need to be precisely geolocated using a precision GPS and need to cover a spatial footprint of at least 10x10m to match the spatial resolution of contemporary satellites like Copernicus Sentinels. As illustrated in the previous section of the report, the reliability of such satellite-based maps would need to be explored and quantified before the maps can be used for management purposes.

At present, the dominant, major nature type (e.g. *open fen* or *bog*) is recorded for each ANO-locality. This vegetation-based classification is likely useful for upscaling using satellite-based machine learning models but adding information about mire massif types (hydromorphological classification) is likely even more useful. Both the mire massif types, and the major nature types are defined in Nature in Norway – NiN (Halvorsen et al. 2020) and can be used in mapping. Hence, we suggest recording mire massif type as part of the ANO-monitoring. In intact areas the mire massif types are generally stable across centuries, so in most cases it will suffice recording this information once.

Assuming we had a national soil biogeochemistry survey dataset for mires in 3-5 years' time, we propose a rough budget frame for producing a pilot national map of soil C and N stocks: Option 1: 500 to 800k NOK – using the same data outlined in section 2 of this report. Option 2: 800 to 1200k NOK – using the same data outlined in section 2 plus additional satellite data from Planet Labs. Option 2 would involve purchasing 3m resolution PlanetScope imagery which gives richer temporal information which can capture phenological differences in mire types and could increase the accuracy of mire C and N stock maps.

3.4 Build up competence for remote sensing and modelling techniques

Remote sensing and spatial modelling competence in needed to characterize 1) peatland area/extent: Use of satellite-based methods to characterize and map peatland areas will provide necessary tools for improving existing knowledge rapidly and relatively cost-efficiently (e.g. Bakkestuen et al. 2023) peatland types: the type of mire is an important predictor of biogeochemistry and is therefore useful for estimating a range of variables including C stocks. This has been done in other countries including Canada (Amani et al. 2019) which holds promise for its feasibility in Norway.

Accurate quantification of soil carbon stocks will require spatially representative and relatively intensive depth measurements, which currently are primarily done manually. New techniques that involve technology to perform proximal sensing of peatland condition are evolving (Minasnay et al. 2023). The term "proximal sensing" denotes sensors that function near the Earth's surface, as opposed to remote sensing methods, which detect reflected or emitted radiation from a distance. Proximal geophysical sensors offer precise mapping and characterization of soil properties, providing detailed information at depths ranging from less than a meter to tens of meters. These sensors are commonly employed in geophysical surveys and have undergone testing to determine their effectiveness in measuring peat depth. Examples of such sensors include electrical resistivity tomography (ERT), electromagnetic induction (EMI), and ground-penetrating radar (GPR). See Silvestri et al. (2019) for an example of airborne EM for measuring peat depth in Norway. See Pesdir et al. (2021) for an example of hand-held GPT in Slovenia for measuring peatland depth. These sensors primarily rely on the distinctive properties of peat, such as its high organic matter content, significant porosity, and elevated water content, resulting in low electrical conductivity. Most of those techniques are under development and the uncertainty introduced by them is unknown. If better calibrated against state-of-the-art methods, they have large potential to simplify and speed up the work needed for characterizing peatland carbon stocks, especially in Norway with partially poorly accessible and heterogeneous landscape.

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Appendix

Table A1. Summary statistics of terrain predictor variables used in Random Forest models for carbon and nitrogen stock.

Type	Variable	N	Mean	Std. Dev.	Min	Max
Terrain	Elevation	312	171	219	3.5	796
	Max Elevation	312	186	220	5.4	802
	Min Elevation	312	158	218	0.1	790
	Slope	312	2.6	2	0.1	15
	Aspect	312	147	41	20	260
	Canopy Height Model	304	0.23	0.28	0.0048	3

Table A2. Summary statistics of climate predictor variables used in Random Forest models for carbon and nitrogen stock.

Type	Variable	N	Mean	Std. Dev.	Min	Max
Climate	Isothermality	307	2.7	0.19	2.2	3.1
	Annual mean precipitation	307	1232	420	456	2412
	Precipitation seasonality	307	29	4.9	17	41
	Precipitation of coldest quarter	307	320	142	93	674
	Precipitation of warmest quarter	307	285	63	160	495
	Precipitation of driest month	307	58	19	18	115
	Precipitation of driest quarter	307	203	75	63	422
	Precipitation of wettest month	307	155	51	55	300
	Precipitation of wettest quarter	307	418	134	163	778
	Annual mean temperature	307	4.4	1.8	-0.2	7.3
	Temperature annual range	307	22	4.8	14	31
	Mean diurnal range	307	5.9	1.1	3.7	7.9
	Temperature seasonality	307	56	13	38	81
	Mean temperature of coldest quarter	307	-2.4	3.4	-10	2.8
	Min temperature of coldest month	307	-5.5	3.9	-14	0.81
	Mean temperature of warmest quarter	307	12	1.2	8.3	15
	Max temperature of warmest month	307	16	1.6	12	20
	Mean temperature of driest quarter	307	3.7	5	-7.6	8.4
	Mean temperature of wettest quarter	307	5.7	3.2	0.13	13

Table A3. Summary statistics of biological predictor variables used in Random Forest models for carbon and nitrogen stock.

Type	Variable	N	Mean	Std. Dev.	Min	Max
Biological	Median blue band reflectance	312	411	83	257	964
	Median green band reflectance	312	631	87	445	1059
	Median red band reflectance	312	676	138	317	1252
	Median R1 reflectance	312	1256	163	904	1838
	Median R2 reflectance	312	2291	300	1535	3787
	Median R3 reflectance	312	2645	354	1788	4447
	Median NIR reflectance	312	2917	382	1930	4918
	Median SWIR1 reflectance	312	1987	213	1333	2607
	Median SWIR2 reflectance	312	1077	129	744	1524
	NBR standard deviation	312	0.13	0.049	0.063	0.4
	Spring NDVI	312	0.37	0.2	-0.083	0.65
	Fall NDVI	311	0.63	0.096	-0.0032	0.9
	Summer NDVI	312	0.63	0.079	0.25	0.85
	5th percentile of NDVI	312	0.26	0.22	-0.99	0.59
	25th percentile of NDVI	312	0.5	0.13	-0.045	0.72
	Median NDVI (50th percentile)	312	0.61	0.079	0.24	0.83
	75th percentile of NDVI	312	0.69	0.066	0.3	0.88
	95th percentile of NDVI	312	0.74	0.059	0.4	0.93
	NDVI texture standard deviation	312	0.041	0.014	0.012	0.11
	5th percentile of NDSI	312	-0.62	0.07	-1	-0.36
	25th percentile of NDSI	312	-0.56	0.044	-0.64	-0.28
	Median NDSI (50th percentile)	312	-0.53	0.05	-0.6	-0.24
	75th percentile of NDSI	312	-0.4	0.23	-0.57	0.84
	95th percentile of NDSI	312	0.13	0.48	-0.49	0.98
	Median dual-polarization ascending orbit	312	-7.6	0.99	-10	-5.6
	Median VH polarization ascending orbit	312	-18	1.1	-21	-15
	VH polarization standard deviation ascending orbit	312	-20	0.87	-23	-17
	Median VV polarization ascending orbit	312	-10	0.91	-13	-7.8
	VV polarization standard deviation ascending orbit	312	-13	0.9	-16	-10
	Median dual-polarization descending orbit	312	-7.5	0.95	-10	-5.7
	Median VH polarization descending orbit	312	-18	1.2	-21	-15
	VH polarization standard deviation in descending orbit	312	-20	0.98	-23	-17
	Median VV polarization in descending orbit	312	-11	0.97	-14	-7.5
	VV polarization standard deviation in descending orbit	312	-14	1.1	-17	-9.3

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2374

NINA Report

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