

# Wall-to-wall mapping of peat depth from Lidar terrain and airborne radiometrics in Norwegian landscapes

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**Abstract.** The abstract goes here. It can also be on *multiple lines*.

## 1 Introduction

Introduction text goes here. Read Gatis et al. (2019) and related work (Minasny et al., 2019).

## 2 Materials and methods

### 5 2.1 Sites

We assessed how well we could predict peat depth at two sites with conspicuously different physical geography: Skrimfjella in eastern Norway and Ørskogfjellet in western Norway (Fig. 1c). These sites were chosen because they were covered by radiometric data from airborne surveys, relatively little built-up area, and road access.

At Skrimfjella we delineated a study area of 34 km<sup>2</sup> based on radiometric coverage and accessibility (Fig. 1b). The study  
10 area has a diverse bedrock, with 32 % alkali feldspar granite, 26 % mergelstein, 10 % granite, and eight other types with > 1 % coverage (NGU, 1:250 000 dataset). The landscape within our delineation is classified as *inland hills and mountains* (Simensen et al., 2021). It is almost without human infrastructure, dominated by forest, and borders on a large nature reserve. The study area has a mean elevation of 438 m above sea level (range 223–711, IQR 351–509), and its mean slope at 10 m resolution is 10.8° (IQR 4.6–15.1°). In Norway’s AR5 national land capability dataset (Ahlstrøm et al., 2019), 1.5 km<sup>2</sup> (4.5 %) of the study  
15 area is classified as mire — defined as areas with mire vegetation and at least 30 cm of peat depth.

At Ørskogfjellet we defined a study area of 124 km<sup>2</sup> which basically followed the footprint of the radiometric survey (Fig. 1a). According to the Geological Survey of Norway, bedrock in the area is 84 % granitic gneiss, 11 % granite, and 5 % aluminium silicate gneiss (NGU, 1:250 000 dataset). This study area comprises a wide range of major landscape types: *coastal plains*, *coastal fjord*, *inland valleys*, as well as *inland hills and mountains* (Simensen et al., 2021). It is mostly forested, but  
20 also contains considerable farmland and open upland, and has several large lakes. Its mean elevation is 211 m above sea level



**Figure 1.** Study areas at Ørskogfjellet (a) and Skrimfjella (b) within southern Norway (c). Land cover shown here is from the AR50 national land resource database and has simplified geometry with respect to the AR5 database used in the study.

(range 0–807, IQR 73–310), and its mean slope at 10 m resolution is 13.0° (IQR 4.7–18.3°). The AR5 dataset counts 15.3 km<sup>2</sup> (12.4 %) of the study area as mire.

## 2.2 Peat depth measurements

At both study sites, our measurements of peat depth were made for the purpose of training a machine learning model of peat depth, and we designed our sampling with this in mind (Brus, 2019). Broadly, we aimed for a sample that was representative the predictor space of the most important predictors of peat depth (Wadoux et al., 2019; Ma et al., 2020). A sample that preserves the properties of the multivariate distribution of predictor and outcome variables is most likely to maintain any complex, non-linear relationships that exist in the population while avoiding spurious ones (Brus, 2019). We chose for our sampling and modelling a spatial resolution of 10 m. We considered this a reasonable compromise between digital terrain model resolution (1 m) and small mires on the one hand, and airborne radiometric resolution (50 m) on the other.

### 2.2.1 Skrimfjella

We measured peat depth in selected locations (10 m raster cells) at Skrimfjella. The locations were chosen only from areas delineated as mire in the AR5 national land capability dataset. Within this mire area, we stratified our sample across values of elevation, slope, and potassium ground concentration (from processed airborne gamma ray spectrometry, Baranwal et al., 2013). Specifically, we used the *eSample* function in the *iSDM* R package (v.1.0) to chose an environmentally systematic sample. This function defines the environmental space as a two-dimensional convex hull around the ordinated data, then creates a regular grid across that space, and lastly finds for each grid cell the datum that is nearest (Hattab et al., 2017). Elevation was extracted from the 10 m national digital terrain model, slope calculated in degrees, and potassium ground concentration downsampled with bilinear resampling. We set a target sample size of 100, excluded the top and bottom percentile from the convex hull, and with these parameters *eSample* returned 105 raster cells.

In addition to the peat depth locations, we had another arm of our sampling design for measuring peatland occurrence, as binary variable. We wanted to measure peatland occurrence outside of mapped mire areas because the AR5 dataset is known to underestimate peatland coverage (especially in forests, Bryn et al., 2018), and because airborne radiometrics may help identify unmapped peatland (Gatis et al., 2019; O’Leary et al., 2022). The occurrence locations were sampled from the part of the study area that (1) was mapped as something other than mire in the AR5 database and (2) had a slope < 20°. We performed environmentally systematic sampling of this population with the same procedure as for the depth locations, and *eSample* returned 106 raster cells.

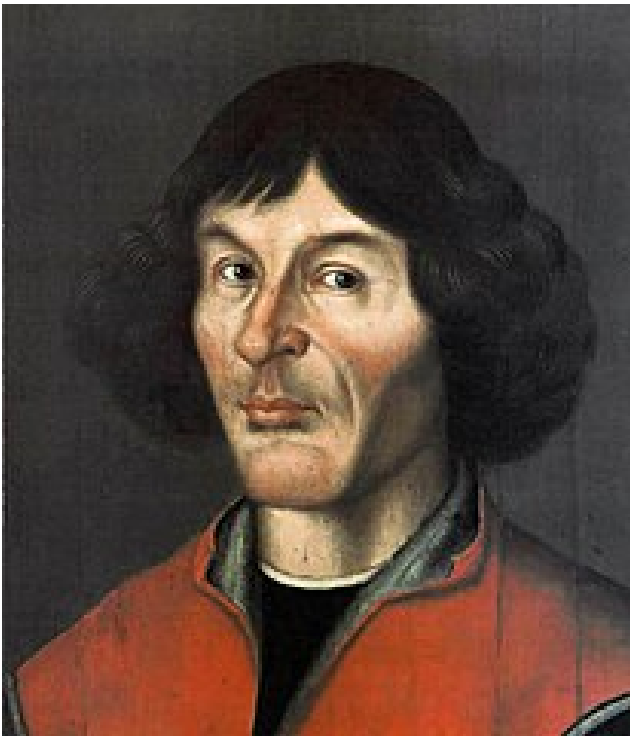
Field work at Skrimfjella was conducted in August 2020. We navigated to the centers of the raster cells in the depth and occurrence samples by handheld GPS, checking that positional error was below 3 m. For each depth sample location, we measured peat depth three times (at the vertices of a triangle with 2 m sides) to get a more representative value for the 10 m raster cell, and to dampen the effect of outlying measurements (Parry et al., 2014). We used a metal probe pushed downward until resistance indicated the base of the peat column. Probe locations were adjusted up to 20 cm if the base of the peat column seemed to be blocked by an obvious artifact. For each occurrence sample location, we recorded the presence or absence of

peatland — primarily by digging and examining the top 20 cm of soil (where this was possible). We judged whether the soil  
55 was a peat soil based on its density, texture, and color. Occasionally, when the soil itself was difficult to judge, we made our  
determination also based on the presence or absence of mire vegetation. Although peat soil is strictly defined by organic content  
(which we did not analyse), we believe our protocol produced reasonable determinations of presence or absence that would  
generally satisfy most of the varying definitions of peatland (Minasny et al., 2023).

Besides the depth and occurrence measurements described above, we also measured peat depth in three subjectively-chosen,  
60 individual mires, using ground-penetrating radar (GPR). We used the Malå ProEx GPR system (Guideline Geo AB, Sweden)  
with its 500 MHz shielded antenna mounted in a plastic sledge, and its control unit connected to a GNSS receiver. At each of  
the three mires we recorded GPR traces along walking transects that covered the extent of the mire, mostly in traversing, zigzag  
patterns with between 5 m and 20 m spacing at their vertices. Along the GPR transects we also probed peat depth at marked  
trace locations, to be able to calibrate the GPR wave speed velocity. We processed the GPR data with Reflex2DQuick software  
65 (v.3.0; Sandmeier Scientific Software, Germany), applying a time-zero correction, a dewow filter, and a gain filter based on  
observed energy decay. Then we picked strong reflectors in the radargrams that we interpreted as the base of the peat column.  
We used picks at marked trace locations to calibrate wave speed velocity; we pooled calibration points across the three mires  
and fitted a linear regression of depth on one-way travel time with the intercept fixed at zero. In total we had 46 calibration  
points along 3.5 km of GPR transects. Finally, we used the calculated wave velocity ( $0.0387 \text{ m ns}^{-1}$ ,  $R^2 = 0.874$ ) to convert  
70 the travel times of all picks to calibrated peat depths.

### 2.2.2 Ørskogfjellet

At Ørskogfjellet we also measured peat depth in a sample of 10 m raster cells, selected from the part of the study area classified  
in the AR5 dataset as mire. Before selecting locations, we determined a minimal sample size that would adequately capture the  
terrain and radiometric properties of the entire mire area. Specifically, we aimed to identify the size at which adding locations  
75 produced diminishing decreases in divergence between sample and population distributions — i.e. the elbow point in a curve  
of similarity between sample and population (Malone et al., 2019). This approach has been found to identify sample sizes that  
correspond with diminishing returns in predictive model performance on external evaluation data (Saurette et al., 2023). We  
defined a sequence of increasing sample sizes (50–500) and for ten replicate samples at each size (drawn by conditioned latin  
hypercube sampling, Minasny and McBratney, 2006; Roudier, 2011), we calculated the mean Kullback-Leibler divergence  
80 between sample and population distributions (Malone et al., 2019; Saurette et al., 2023). The variables in the divergence  
calculation were terrain slope and four radiometrics: potassium, thorium, uranium, and total count. Next, we fitted a asymptotic  
regression of mean divergence on sample size, and identified the sample size at which the curve reached 95 % of the fitted  
asymptote. Through this procedure we found that we could adequately capture the population distribution with a sample of  
160 locations.



**Figure 2.** one column figure

**Table 1.** TEXT

a	b	c
1	2	3

Table Footnotes

85 **2.3 Peat depth predictors**

**2.4 Predictive models of peat depth**

**3 Results**

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**3.1 Tables**

90 You can add `\LaTeXtable` in an R Markdown document to meet the template requirements (Table 1).

Or you can use markdown to create the table with `booktabs = FALSE` (<https://github.com/rstudio/rarticles/issues/558#issuecomment-19079>)

**Table 2.** My caption

	mpg	cyl	disp
Mazda RX4	21.0	6	160
Mazda RX4 Wag	21.0	6	160
Datsun 710	22.8	4	108

See Table 2.

**4 Discussion**

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**5 Conclusions**

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. *Code and data availability.* Use this to add a statement when having data sets and software code available

**Appendix A: For submission**

105 “Appendices: all material required to understand the essential aspects of the paper such as experimental methods, data, and interpretation should preferably be included in the main text. Additional figures, tables, as well as technical and theoretical developments which are not critical to support the conclusion of the paper, but which provide extra detail and/or support useful for experts in the field and whose inclusion in the main text would disrupt the flow of descriptions or demonstrations may be presented as appendices. These should be labelled with capital letters: Appendix A, Appendix B etc. Equations, figures and  
110 tables should be numbered as (A1), Fig. B5 or Table C6, respectively. Please keep in mind that appendices are part of the manuscript whereas supplements (see below) are published along with the manuscript.”

## Appendix B: Figures and tables in appendices

Please also sort the appendix figures and appendix tables into the respective appendix sections. They will be correctly named automatically.

## 115 Appendix C: Copernicus from Rmarkdown

**Please note:** Per their guidelines, Copernicus does not support additional  $\LaTeX$  packages or new  $\LaTeX$  commands than those defined in their `.cls` file. This means that you cannot add any extra dependencies and a warning will be thrown if so. **Important:** Always double-check with the official manuscript preparation guidelines at [https://publications.copernicus.org/for\\_authors/manuscript\\_preparation.html](https://publications.copernicus.org/for_authors/manuscript_preparation.html), especially the sections “Technical instructions for LaTeX” and “Manuscript  
120 composition”. Please contact Daniel Nüst, `daniel.nuest@uni-muenster.de`, with any problems.

. *Author contributions.* JV: Conceptualization, Investigation, Data curation, Formal analysis, Writing – original draft. NG: Conceptualization, Methodology, Writing - review & editing. MKG: Investigation, Writing - review & editing. KKM: Investigation, Data curation, Writing - review & editing. SDN: Investigation, Writing - review & editing. KR: Conceptualization, Investigation, Writing - review & editing. MS: Investigation, Data curation, Writing - review & editing.

125 . *Competing interests.* The authors declare that they have no conflict of interest.

. *Disclaimer.* The authors declare that the results, discussions, and interpretations presented in this study are solely their own. The views expressed herein do not necessarily reflect those of their respective institutions or funding agencies.

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