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

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 $34 \, \text{km}^2$ based on radiometric coverage and accessibility (Fig. 1b). 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 $438 \, \text{m}$ above sea level (range 223–711, IQR 351–509), and its mean slope at $10 \, \text{m}$ resolution is $10.8°$ (IQR 4.6–15.1°). In Norway's AR5 national land capability dataset (Ahlstrøm et al., 2019), $1.5 \, \text{km}^2$ (4.5 %) of the study area is classified as mire — defined as areas with mire vegetation and at least $30 \, \text{cm}$ of peat depth.

At Ørskogfjellet we defined a study area of $124 \, \text{km}^2$ which basically followed the footprint of the radiometric survey (Fig. 1a). 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 also contains considerable farmland and open upland, and has several large lakes. Its mean elevation is $211 \, \text{m}$ above sea level (range 0–807, IQR 73–310), and its mean slope at $10 \, \text{m}$ resolution is $13.0°$ (IQR 4.7–18.3°). The AR5 dataset counts $15.3 \, \text{km}^2$ (12.4 %) of the study area as mire.

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.

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 $10\,\text{m}$. We considered this a reasonable compromise between digital terrain model resolution ($1\,\text{m}$) and small mires on the one hand, and airborne radiometric resolution ($50\,\text{m}$) on the other.

2.2.1 Skrimfjella

We measured peat depth in selected locations ($10\,\text{m}$ 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 $10\,\text{m}$ national digital terrain model, slope calculated in degrees, and potassium ground concentration downscaled 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 $3\,\text{m}$. For each depth sample location, we measured peat depth three times (at the vertices of a triangle with $2\,\text{m}$ sides) to get a more representative value for the $10\,\text{m}$ 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 $20\,\text{cm}$ 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 $20\,\text{cm}$ of soil (where this was possible). We judged whether the soil was a peat soil based on its density, texture, and color. Occasionally, when the soil itself was difficult to judge, we made our
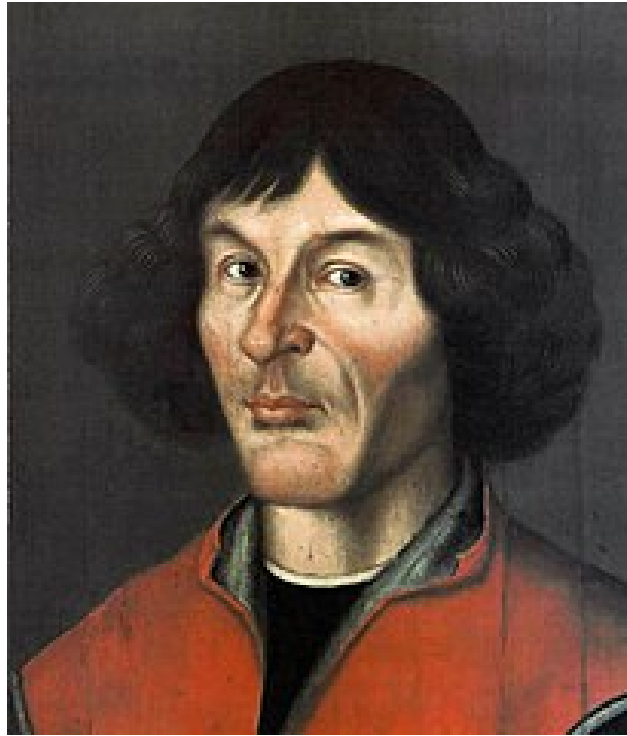
Figure 2. one column figure

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).

GPR data.

2.2.2 Ørskogfjellet

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2.3 Peat depth predictors

2.4 Predictive models of peat depth

3 Results

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Table 1. TEXT

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Table Footnotes

Table 2. My caption

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3.1 Tables

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4 Discussion

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5 Conclusions

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Appendix A: For submission

"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 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.

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, especially the sections "Technical instructions for LaTeX" and "Manuscript composition". Please contact Daniel Nüst, `daniel.nuest@uni-muenster.de`, with any problems.

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