Author response to Editor

EC1: David Dunkerley, 28 Jun 2022

This paper presents a study that sought to revise the mapping of peat soils at national scale across Sweden.

The 'Methods' section reports that the primary data used are detailed elevation data from airborne laser scanning (at 2 m resolution), and a computed soil moisture map previously developed by Ågren et al. The soil moisture map in turn relied on unspecified 'digital terrain indices' (ms. line 143-144), together with "ancillary data on quaternary deposits, soil depth, annual and seasonal runoff etc " (ms. line 145) that were used as input for a machine learning model, to predict soil moisture across Sweden. This section of the Methods presentation seemed inadequate to me. 1) What were the topographic indices? 2) How and at what scale were they derived? 3) How were annual and seasonal runoff quantified, and what was the resolution and quality of these data? 4) Runoff data can surely have been at no finer scale than that of catchment level, in most cases. If so, how can it assist in mapping peat at 2 m resolution? The authors need to explain much more thoroughly the data used and the methods used in the machine learning model. 5) In turn, more commentary was needed on the resolution and quality of the soil moisture maps. 6) What, for instance, is the extent of seasonal variability? 7) Is the parameter calculated perhaps an annual mean or median value?

Author response:

Thank you for your feedback. We answered each question below:

Question: What were the topographic indices? How and at what scale were they derived?

Response: *For producing the soil moisture map, we included a total of 45 input variables a.k.a. features, which were mostly derived from ALS data. However, after performing the feature reduction procedure, which is a common procedure of developing machine learning models, a total of 28 features remained in the final model. The variables highlighted in black in the table below were used to derive the SLU soil moisture map.*

Here, we also report some relevant texts from (Ågren et al., 2021) to answer the question regarding how and at what scale the predictor variables were developed:

"The soil moisture and local topography measures were all calculated from the 2 m national DEM, apart from the Topographic Wetness Index (TWI), which has been found to give unrealistic results when calculated at high resolution (Sørensen and Seibert, 2007, Ågren et al., 2014b). Therefore, TWI was calculated at coarser resolutions (10–48 m) deemed sufficient to capture the macro-topographical control of hydrological pathways. By including different window sizes (6 × 6 m to 160 × 160 m) we evaluated both macro- and micro-topographic effects on these pathways (Table 2). However, as we were applying substantially higher resolution than many other studies, it also enabled us to evaluate the modeling utility of more 'small-scale features'. For this purpose we incorporated the following digital terrain indices in addition to those described by (Lidberg et al., 2020)—the downslope index (Hjerdt et al., 2004), standard deviation of mean elevation within a moving window of 7 × 7 DEM cells, standard deviation from slope with a moving window of 3 × 3 cells, circular variance of aspect with a 3 × 3 moving window, and ruggedness index—all calculated from the 2 m DEM. For an explanation of these indices see the WhiteboxTools User Manual (Lindsay,

2020). By including more of these 'small-scale features' we aimed to improve the modelling of soil moisture in local pits and small-scale variability in riparian zones. Ancillary environmental variables used to capture variability in climatic and soil conditions were: quaternary deposits and soil depth from the Swedish Geological Survey; wetlands from the Swedish Mapping, Cadastral and Land Registration Authority; runoff from the Swedish Metrological and Hydrological Institute; and land-use from the national land cover database as well as a 10 m resolution soil moisture index from the Swedish Environmental Protection Agency (SEPA). These data, summarized in (Table 2), were resampled to 2 m grids to match the LIDAR-derived variables."

Table 2. Input variables used to model soil moisture, including digital terrain indices and ancillary environmental variables, calculated as described by [1](Lidberg et al., 2020) and [2](Lindsay, 2020). Abbreviations refer to the designations in Figure 4. Features included in the final model are marked in black and features that were evaluated but excluded from the final model are marked in grey.

In-data map layers used to classify soil moisture	Utilized scales, thresholds and seasons	Data source	Short name
Soil moisture measures			
Depth to water 0.5 ha [1]	Stream initiation threshold 0.5 ha	Calculated from the 2 m DEM	DTW 0.5 ha
Depth to water 1 ha [1]	Stream initiation threshold 1 ha	Calculated from the 2 m DEM	DTW 1 ha
Depth to water 2 ha [1]	Stream initiation threshold 2 ha	Calculated from the 2 m DEM	DTW 2 ha
Depth to water 5 ha [1]	Stream initiation threshold 5 ha	Calculated from the 2 m DEM	DTW 5 ha
Depth to water 10 ha [1]	Stream initiation threshold 10 ha	Calculated from the 2 m DEM	DTW 10 ha
Depth to water 15 ha [1]	Stream initiation threshold 15 ha	Calculated from the 2 m DEM	DTW 15 ha
Depth to water 30 ha [1]	Stream initiation threshold 30 ha	Calculated from the 2 m DEM	DTW 30 ha
Down slope index [2]	2 m drop threshold	Calculated from the 2 m DEM	DI 2 m
Topographic wetness index [1]	10 m × 10 m	Calculated from a 10 m DEM resampled to 2 m	TWI 10 m
Topographic wetness index [1]	24 m × 24 m	Calculated from a 24 m DEM resampled to 2 m	TWI 24 m
Topographic wetness index [1]	48 m × 48 m	Calculated from a 48 m DEM resampled to 2 m	TWI 48 m
Elevation above stream 0.5 ha [1]	Stream initiation threshold 0.5 ha	Calculated from the 2 m DEM	EAS 0.5 ha
Elevation above stream 1 ha [1]	Stream initiation threshold 1 ha	Calculated from the 2 m DEM	EAS 1 ha
Elevation above stream 2 ha [1]	Stream initiation threshold 2 ha	Calculated from the 2 m DEM	EAS 2 ha
Elevation above stream 5 ha [1]	Stream initiation threshold 5 ha	Calculated from the 2 m DEM	EAS 5 ha

Elevation above stream 10 ha [1]	Stream initiation threshold 10 ha	Calculated from the 2 m DEM	EAS 10 ha
Elevation above stream 15 ha [1]	Stream initiation threshold 15 ha	Calculated from the 2 m DEM	EAS 15 ha
Elevation above stream 30 ha [1]	Stream initiation threshold 30 ha	Calculated from the 2 m DEM	EAS 30 ha
Local topography measures			
Elevation [1]	Elevation of each field plot	Calculated from the 2 m DEM	Elevation
Standard deviation from mean elevation [2]	Standard deviation from mean elevation with a 7 x 7 cell moving window	Calculated from the 2 m DEM	DFME
Standard deviation from elevation [1]	Standard deviation from the digital elevation model with a 5 x 5 cell moving window	Calculated from the 2 m DEM	STDV 5 Cells
Standard deviation from elevation [1]	Standard deviation from the digital elevation model with a 10 x 10 cell moving window	Calculated from the 2 m DEM	STDV 10 Cells
Standard deviation from elevation [1]	Standard deviation from the digital elevation model with a 20 x 20 cell moving window	Calculated from the 2 m DEM	STDV 20 Cells
Standard deviation from elevation [1]	Standard deviation from the digital elevation model with a 40 x 40 cell moving window	Calculated from the 2 m DEM	STDV 40 Cells
Standard deviation from elevation [1]	Standard deviation from the digital elevation model with a 80 x 80 cell moving window	Calculated from the 2 m DEM	STDV 80 Cells
Standard deviation from slope [2]	Standard deviation from slope with a 3 x 3 cell moving window	Calculated from the 2 m DEM	SDFS

Circular variance of aspect [2]	Circular variance of aspect with a 3 x 3 cell moving window	Calculated from the 2 m DEM	CVA
Ruggedness [2]	Ruggedness index	Calculated from the 2 m DEM	Ruggedness
Slope [2]	Slope	Calculated from the 2 m DEM	Slope
Ancillary environmental variables			
Quaternary deposits - Peat Soil [1]	Extracted from the best map available at each field plot (with scales differing among regions)	Digital map from the Geological Survey of Sweden	Peat Soil
Quaternary deposits – Glacial till [1]	-||-	-||-	Till soil
Quaternary deposits - Fine sediment [1]	-||-	-||-	Fine sediment
Quaternary deposits – Coarse Sediment [1]	-||-	-||-	Coarse sediment
Quaternary deposits - Thin soil [1]	-||-	-||-	Thin soil
Soil depth	Modelled soil depth	-||-	Soil depth
Wetlands from the Swedish property map [1]	1:12 500 scale	From the Swedish Mapping, Cadastral and Land Registration Authority	Wetlands
Winter Runoff [1]	30-year average winter runoff	Digital map from Swedish Metrological and Hydrological Institute, Calculated with S-HYPE	Winter Runoff
Summer Runoff [1]	30-year average summer runoff	-||-	Summer Runoff
Autumn Runoff [1]	30-year average autumn runoff	-||-	Autumn Runoff
Annual Runoff [1]	30-year average annual runoff	-||-	Annual Runoff
Spring Runoff [1]	30-year average spring runoff	-||-	Spring Runoff
X Coordinates of field plots [1]	X coordinates in SWEREFF 99 TM	NFI	X Coordinate

Y Coordinates of field plots [1]	Y coordinates in SWEREFF 99 TM	NFI	Y Coordinate
National land use data	10 m x 10 m	Swedish Environmental Protection Agency	CORINE
Soil moisture index	10 m x 10 m	Swedish Environmental Protection Agency	SMI

Question: How were annual and seasonal runoff quantified, and what was the resolution and quality of these data?

Response: *The annual and seasonal runoff were estimated using Hydrological Predictions for the Environment (HYPE) model, specifically S-HYPE which is the modified HYPE model for Swedish condition. S-HYPE is particularly suited for Sweden since there is a considerable variability in runoff conditions across different regions of Sweden and across different seasons. Here, S-HYPE was used to model seasonal and annual runoff in 33 605 sub-catchments across Sweden between 1982 and 2015. The modelled runoff was then designated as "Spring", "Summer", "Autumn", "Winter", and "Average". More details on this analysis was reported in our paper (Ågren et al., 2021).*

Question: Runoff data can surely have been at no finer scale than that of catchment level, in most cases. If so, how can it assist in mapping peat at 2 m resolution?

Response: *Yes the runoff data is modelled on a Sub-catchment scale (33 605 sub-catchments across the country, see map below under question 6). During the development of the SLU soil moisture map we included data capturing the controls on soil moisture in multiple scales, from regional weather patterns, down to local topography controlling how water is routed locally through the landscape. Our XGBoost model was trained using ca 16 000 field observations across the country and was built using 73 000 multiband raster stacks where each raster stack had a footprint of 2.5 km2 (i.e. the size of the original laser tiles). By resampling all 45 input-grids to 2 m grids to match the LIDAR-derived variables, we could allow the machine learning model to learn at what scale the major control on soil moisture appeared. While the runoff data (seasonal or annual) could be uniform within a tile it can help explain the variability between tiles in the model (i.e. large scale controls on soil moisture). Depth-to-water maps on the other hand showed a higher variability within a tile, but was in general "more uniform" between tiles across the country. It helped explain within tile variability in the model (i.e. local scale variability). In the feature reduction procedure variables that did not contribute significantly in predicting the soil moisture was removed from the model. Out of the evaluated 45 features, 28 were included in the final predictive model used to produce the SLU soil moisture map.*

We showed that soil moisture is controlled on many scales. The terrain indices Depth-to-water and Topographic wetness index was the most important features for predicting soil moisture (Fig. 4A from Ågren et al., 2021) ("more within-tile local scale variability"). When it came to the seasonal weather patterns, autumn, summer and winter runoff contributed significantly and was included in the final predictive model (Fig. 4A from Ågren et al., 2021) ("more larger scale weather pattern, between tile variability").

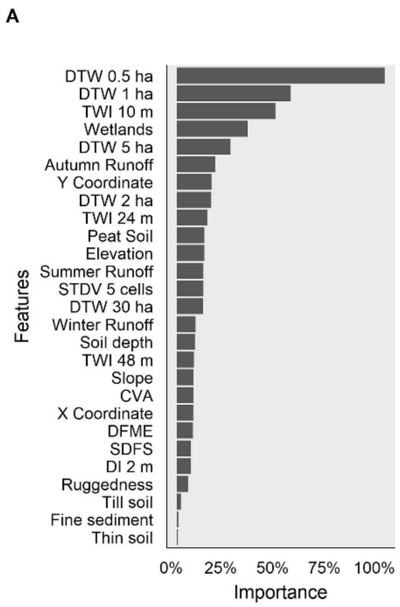

Fig. 4A from Ågren et al 2021. Variable importance of the 28 input features for the 2-class (A) XGBoost model. The variable names are explained in Table 2. Note that the variable Coarse sediment was removed from the graph, as it was so close to 0 that the column became invisible.

Question: In turn, more commentary was needed on the resolution and quality of the soil moisture maps.

Response*: In the revised manuscript, we will add more information on how the model was trained and tested, to give more background on the quality measures (kappa and MCC).*

Question: What, for instance, is the extent of seasonal variability?

Response: *See Figure 2 from (Lidberg et al., 2020) where (B) illustrates average winter runoff from the last +30 years and (C) average spring runoff from the last +30 years. Based on runoff modelling on >33000 subcatchments.*

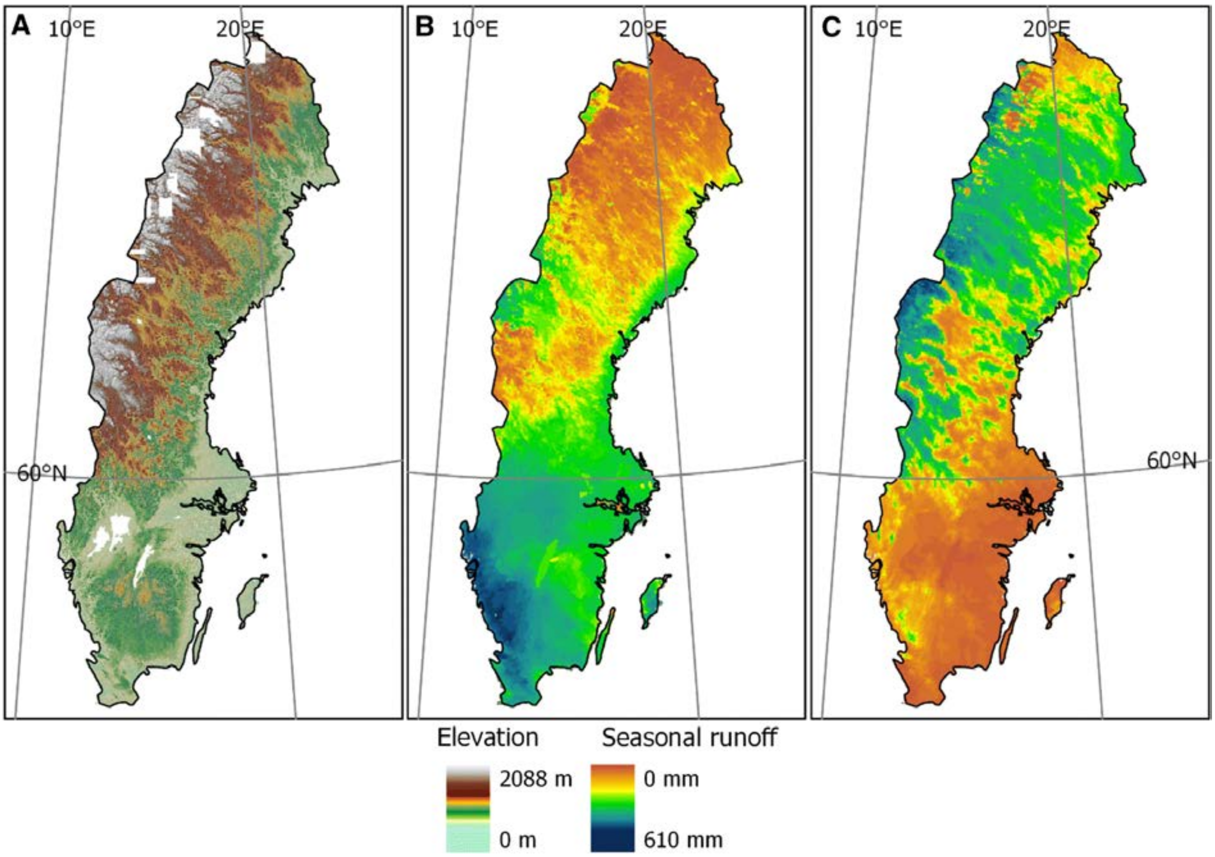

Figure 2 from Lidberg et al., 2020. An example of the variability of the landscape and climate in Sweden that could affect the hydrological modelling ("Other factors affecting the hydrological modelling"). Here exemplified by (A) the Swedish national DEM, (B) average winter runoff from the last 30 years and (C) average spring runoff from the last 30 years.

Question: Is the parameter calculated perhaps an annual mean or median value?

***Response**: Runoff was modeled using S-Hype on a daily timestep, then summarized annually/seasonally, then averaged over the +30 year period.*

Question: The authors need to explain much more thoroughly the data used and the methods used in the machine learning model.

***Response**: As asked in the previous questions as well, we decided to expand the method section slightly to describe the production of soil moisture, however, for more detailed method description, we refer the readers to our recent papers; i.e. (Ågren et al., 2021; Lidberg et al., 2020). We now suggest to include the section below in the revised manuscript.*

"2.3 Generating categorical (peat vs. mineral soils) and continuous organic layer thickness maps

This study utilized the SLU (Swedish University of Agricultural Science) soil moisture map that exhibits soil moisture variation across Sweden on an arbitrary scale from 1 to 100 i.e. from dry to wet (Ågren et al., 2021). The detailed methodology for producing the SLU soil moisture map was reported in (Ågren et al., 2021) and a previos verison of the map in (Lidberg et al., 2020). Here we give a brief introduction to the SLU soil moisture map. It was developed using a combination of digital terrain indices (derived from 2 m resolution digital elevation model based on airborne laser scanning data

(ALS) and ancillary data on quaternary deposits, soil depth, annual and seasonal runoff. The topographical indices were calculated on window sizes from 6 × 6 m to 160 × 160 m to allow for both large scale and small scale controls on soil moisture. By working on a higher resolution than most other studies, we aimed to improve the modelling of soil moisture in local pits and better capture the small-scale variability in riparian zones. In total, 45 different predictors (aka features) were evaluated for predicting soil moisture and after the feature reduction process, 28 predictors were remained in the final model. The predictors were utilized in an Extreme Gradient Boosting model (Chen et al., 2020) to predict the soil moisture across Sweden. The top predictors included Depth-To-Water index and Topographic Wetness Index calculated at different scales and resolutions, but also the autumn runoff and latitude (Ågren et al., 2021). The produced maps are now publicly available at www.slu.se/mfk. The model was trained and tested using 19 643 field observations from the NFI of which 80% were used for training and 20% was used for testing. The soil moisture map has Cohen's Kappa (Cohen, 1960) and Matthews Correlation Coefficient (MCC) (Matthews, 1975) values of 0.69 and 0.68, respectively. "

Question: The predicted soil moisture data were then related to field-mapped peat depths collected from forestry surveys in which pits were excavated, and a regression model was fitted to the data. This is then used to predict peat thicknesses elsewhere across Sweden. However, the relationship between predicted organic layer thickness and measured thickness from the field survey data (Figure 4 in the ms.) shows enormous scatter. The bulk of the data points appear to be for quite thin organic layers (bottom left-hand corner of Fig 4), with relatively few observations > 60 cm (right hand part of Fig 4).

***Response**: The aim of this study was to develop and evaluate a new method for delineating the horizontal distribution of peat. Despite some limitations of the proposed method, it predicts the majority of the observations correctly and provides an effective approach for predicting peat distribution at a landscape scale. Due to the overlap of the points in the figure, it was difficult to detect this pattern. Therefore, we now revised the figure to include the quadrants of the confusion matrix, using ≥50 cm peat as an example. If we take the example of delineating peat with ≥50 cm depth, it is true that the model misclassifies peat as mineral soil in 104 instances (FN) and misclassifies mineral soils as peat in 135 cases (FP) But, 427 observations are correctly classified as peat and 2217 are correctly classified as mineral soils. 2644 of 2883 soil pits are correctly classified in this example. This gives the ≥50 cm peat map a higher overall quality (Kappa and MCC) than the topographic and Quaternary deposits maps. These findings highlight that the prediction was substantially better than what was deemed in the previous version of Figure 4.*

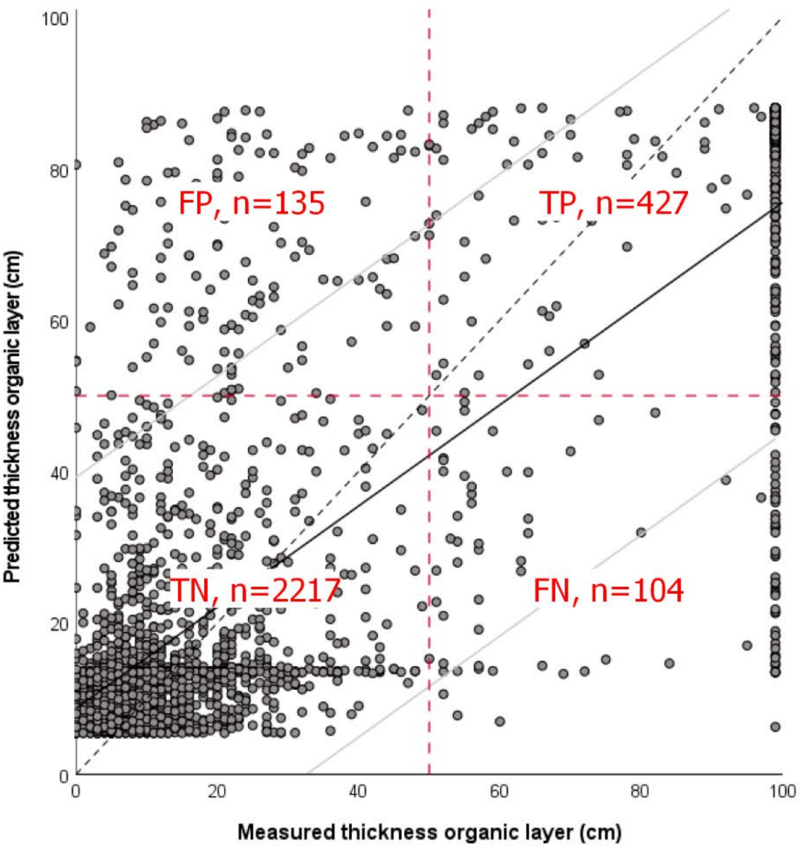

Figure 4 from the article with the quadrants for the confusion matrix highlighted in red, here using ≥50 cm peat as an example. Predicted vs measured continuous thickness of the organic layer in the evaluation dataset (n = 2 883). Dashed line indicate the 1:1 line and black line a linear regression (R^2 = 0.67, p<0.001), grey lines indicate 95% CI. Field measurements of peat thickness that were 99 cm or above were reported as 99 cm, hence the many over lapping data points.

Question: The authors do not actually describe the process of producing their predicted organic layer maps from the soil moisture data, but rather simply jump from Fig 3 to a discussion of the resulting maps. This needs to be corrected.

Response: *We address the comment by adding this paragraph in the manuscript: "By solving Eq. 7 for X when Y was 30, 40 and 50 cm we could determine the soil moisture limits for classifying peat soil. At organic layer thickness of ≥30, ≥40, and ≥50 cm, the soil moisture limits were ≥76%, ≥83% and ≥87%, respectively (Figure 3). These thresholds were used to reclassify the soil moisture map into maps of peat extent while the remaining soil was delineated as mineral soil. Hence, three different peatland maps were derived, which we referred as "peat ≥ 30 cm", "peat ≥ 40 cm", and "peat ≥50 cm". In addition, a continuous organic layer thickness map was generated by applying Eq. 7 in raster calculator on the continuous soil moisture map. This continuous map does not contain discrete classes of mineral and peat soils, rather, it presents the distribution of organic layer thickness across the landscape."*

Question: Given the enormous scatter in Fig 4, the authors at several places say that their thickness maps should not be 'taken literally' (e.g. line 460, line 466) and yet there is no real quantification of the probable magnitude of error at any location. This could have been done by comparing with the field data acquired from pits. The RMSE was reported as 19 cm (line 306) but this is a huge uncertainty given that most of the organic layers appear to be less than 20-30 cm in thickness. Is this level of uncertainty actually acceptable, and are the predicted depths sufficiently reliable for the estimation of carbon stocks, for instance?

Response*: We deem the level of uncertainty to be satisfactory for the horizontal delineation of peatlands; especially if the continuous map are used to highlight the areas where the delineation is more uncertain, i.e. along the borders of the peatlands. However, given the large RMSE for the depth estimates, and the generally thin layers of organic soils across most of the Swedish forest landscape, we do not suggest to use the depth estimates for carbon stocks. We will clarify this in the discussion.*

Question: Overall, I was left unsure about how much confidence could be placed in the thickness maps generated by the authors. I think that a fuller discussion of actual thicknesses and the likely uncertainty (surely varying with topographic position, and perhaps areal extent of particular organic or peat deposits) in the predictions is required.

Response: *Thank you for your comment, however, providing more details of the thickness map was not within the main scope of the study. Rather, we focused on the horizontal delineation of peat. We will add some text in the discussion to clarify this.*

Question: The authors claim excellent resolution in mapping peat deposits covering just 4 m^2 (e.g. line 405) - i.e., just a single pixel in data at 2 m resolution. Do such tiny peat deposits actually exist? If so, what accounts for their isolated accumulation? The authors need to comment.

Response*: While there exist really small topographic hollows (in the order of 4m2) that can fill up with peat, this is not the typical peat that we were able to map with the new methodology. The visual inspection of the map indicate that the main improvement from traditional maps is that the maps capture the riparian peat, and forested peatlands that were misinterpreted as mineral soil from aerial photos. It also gives a much more accurate delineation of the border between for example a flat mire and surrounding drumlins. This is easy to see based on ALS data while this was more difficult using aerial photos. We will now explain this further in the revised manuscript.*

Question: There are minor errors scattered throughout the ms. In particular, I would suggest that as a formal geological Period, 'Quaternary' should be capitalised. This is written 'quaternary' at many places in the ms., and all instances need correcting. The authors are occasionally inconsistent with this, such that Table 2 for instance contains 'Quaternary' as does the heading for Section 2.4, but elsewhere, mostly lower-case letters are used.

Response*: We will make sure to capitalize Quaternary throughout the manuscript. We will also ensure other necessary minor improvements.*

Additional author comment: *While we were revising our manuscript we found an error in Figure 5. The thickness of the organic layer should range 6-88 cm. Should this article be accepted for publication we will revise the figure and the text in the revised manuscript accordingly.*

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