SOIL Discuss.,
https://doi.org/10.5194/soil-2020-75-AC3, 2021

Interactive comment on "Predicting the spatial distribution of soil organic carbon stock in Swedish forests using remotely sensed and site-specific variables" *by* Kpade O. L. Hounkpatin et al.

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Received and published: 24 February 2021

Dear Reviewer,

Please find enclosed the revision of our manuscript "Predicting the spatial distribution of soil organic carbon stock in Swedish forests using remotely sensed and site-specific covariates" by Hounkpatin et al. We thank you for the very competent review of our paper and the productive comments towards the improvement of our manuscript. We agree with almost all of them and revised the manuscript accordingly.

We hope that our paper is now acceptable for publication in SOIL.

Yours sincerely,

Ozias Hounkpatin

Answers to Reviewer

General comment

The manuscript is well written and generally clear, with an appropriate structure and the information provided in tables and figures is useful and necessary, although I have some specific comments for the presentation of some figures. The length of the paper is appropriate, as the presentation of the results is synthetic, and the discussion gives a concise explanation of the observed results supported by other findings in the SOC literature. This research paper investigated the key variables for predicting soil organic carbon (SOC) stocks in the litter layer, mineral soil, and total SOC of forest soils in Sweden, and maps its spatial distribution using random forest models. The study compares the accuracy of global models (calibrated for the whole study area, Sweden) and local models for north, central and southern Sweden. The calibration data originated from the Swedish National Forest and as predictor variables they compared three different sets: 1) only site variables observed at the sampling plots, 2) remote sensing variables, and 3) all variables. My main comment may be more a suggestion for the follow-up study. Mapping some of the site variables that were more decisive for SOC prediction (soil moisture class, vegetation type, soil type and soil texture) and including them as covariates for mapping may improve the model accuracy for mapping. However, as these variables will be themselves estimated with statistical models, there may be an increase in the uncertainty due to error propagation. Hence, the uncertainty of the map for a model including all variables may be a conservative estimate. Also, in that future scenario, consider that if you calibrate the model with the data observed at the plots but map it with the gridded estimates of the site variables, the accuracy may also overestimated. If you calibrate the model with the gridded predictions for soil moisture class, soil texture, etc., perhaps they may not be as relevant covariates, and maybe the accuracy of the model will not be the highest. I recommend acceptance after minor revisions, for the following sections.

Specific comments L51-53: Maybe you can include geostatistics as part of the modelling methods. - Author′s Response: We thank the reviewer for pointing out “geostatistics” which is also used for DSM. We now included additional citation (Mallik et al., 2020) related to “geostatistics” and mention it along linear models and machine learning. Manuscript lines (see lines 49 – 54): Many studies used DSM approaches for predicting SOC stock at different scales and for various land use/land cover, climate and across a wide range of soil types (Söderström et al., 2016;Tranter et al., 2011;Beguin et al., 2017;Mansuy et al., 2014; Mallik et al., 2020). These studies use different modelling techniques ranging from geostatistics, multiple linear regression to machine learning models such as artificial neural network, support vector machine and boosted regression trees. L55: consider changing “modelling over a large landscape” to “large extent”. - Author′s Response: Correction made Manuscript lines (see lines 55 – 58): The accuracy and precision of predictions resulting from modelling over a large extent are often reported to be poor because of the spatial heterogeneity encompassing different soil types, topography and soil properties (Grimm et al., 2008;Schulp and Verburg, 2009;Schulp et al., 2013;Tang et al., 2017). L66: include soil with “the inclusion of the location coordinates”. - Author′s Response: Correction made Manuscript lines (see lines 65 - 66): Building on the soil state-factor (climate, organisms, relief, parent material, age) equation developed by Jenny (1941), McBratney et al. (2003) introduced the conceptual framework for DSM referred to as SCORPAN which complemented the former with the inclusion of location coordinates. L86-94: This paragraph is somewhat confusing. Does the NFSI run every year or every 5 years? Maybe give a reference for the NFSI or the NFI datasets. - Author′s Response: We are sorry for the lack of clarity of this paragraph. Actually, the permanent plots of NFI are re-inventoried after 5 years and after 10 years for those of NFSI. We now provided citations and remove the 5 years mistakenly attributed to NFSI. Manuscript lines (see lines 49 – 50): The NFSI runs con-

currently every year with the NFI and consist in repeated survey of forest vegetation and soil chemical and physical properties (Stendahl et al., 2017;Ortiz et al., 2013). Lines 96 – 97: Each plot of the NFSI are inventoried once every 10 years. L99-L100: Please, indicate if the content of inorganic carbon in mineral soil is negligible in the study area. - Author′s Response: Due to sufficient leaching pedogenetic carbonates are not formed in Swedish soils. There are a few areas with CaCO3 in sedimentary bedrock where soils can contain some carbonates. However, they cover less than 1% of the Swedish forest area and hence we regard them as negligible in this case. - Manuscript lines (see lines 99 – 103): Soil samples are collected in a subset of the plots with humus sampling on ca. 10 000 plots and mineral soil sampling on c. 4500 plots (Stendahl et al., 2017). Based on the NFSI dataset, pedogenetic carbonates are not formed in these soils due to sufficient leaching and also sedimentary bedrocks which could potentially contain CaCO3 cover less than 1% of Swedish forests. Therefore the content of inorganic carbon in mineral soil is considered negligible in the study area. L104: what type of interpolation? Splines? Linear? - Author′s Response: Thanks for the inquiry. The carbon stocks for each layer with data is calculated. Thereafter the carbon pool is assumed to change linearly between measured layers. Even if the deepest sampled horizon (55-60 cm) is deeper than the top 50 cm it is utilized in the interpolation but the carbon stock below 50 cm is not counted in. Manuscript lines (see lines 107 - 109): The total mineral SOC stock down to 50 cm depth for each site is calculated using the SOC stock of measured layers with empirical model for bulk density (Nilsson and Lundin, 2006), corrections for stoniness (Stendahl et al., 2009) and linear interpolation between measured layers L150: the soil moisture class is later shown as a very important variable. Perhaps you could describe it a bit more. It refers to the frequency of the year it is dry/moist due to the proximity of the water table, or also influenced by soil texture (e.g., soil drainage class)? - Author′s Response: The soil moisture class is determined in the field through field staff judgement of the location of the average ground water table over the vegetation season. The field staff uses indicators of which soil texture is one and others are topographic position and vegetation. -

Manuscript lines (see lines 154 - 157): The records of site characteristics (Table 1) are also carried out during the NFSI. Site description include soil types, soil moisture class, soil texture class, vegetation type and parent material class. The soil classiïňĄcation was based on the World Reference Base (WRB) for soil resources. The location of the average ground water table over the vegetation season was the main criterion for defining classes of soil moisture. L153: The field layer refers to the understory? - Author's Response: Thanks for the question. The field layer refers to the understory, mainly the herbaceous plants. Manuscript lines (see lines 158 - 160): The vegetation type as reported in Table 1 was defined by combining the descriptions of the field layers which refer to the understory. Field layers consisted of four main types which are categorized from fertile to poor, namely herb types (tall or low), grounds without field layer, grass types and dwarf-shrub types. L159: did you also used the QRF models to predict the 5th and 95th percentiles and create the 90% prediction interval? - Author's Response: Yes we took advantage of the capacity of the QRF to compute quantiles of the predictions directly from the bootstrap (bootstrap, aggregation, bagging). Then, the 5th and 95th percentiles were predicted to create the 90% prediction interval. We have added this specific information in our manuscript. Manuscript lines (see lines 249 – 251): The QRF was used to predict all percentiles including the 5th and 95th percentile required to create the 90 %-prediction intervals. Finally, the coverage of the 90 %-prediction intervals by the observation from the validation set was also analyzed. L201-203: I would have used a larger buffer, but I imagine that you assessed that this length was appropriate. Later in the results, I miss some information on how the local maps overlapped, whether or not there was some edge effect. In figure 6 it seems that there were not large differences in the boundaries. - Author's Response: We apologize for this reporting mistake. A 4 km buffer area was actually defined. This has been corrected in the manuscript. Manuscript lines (see lines 208 - 210): A buffer of 4 km was considered for the shapefiles of each subarea to create overlapping zones which ensured smooth transition while merging by averaging the SOC stock values within these shared units. L222-225: This sentence is not very clear. You split the dataset into a calibration (80%)

and independent validation (20%). And then you apply the tenfold cross-validation, repeated 5 times, on the calibration subset, right? - Author's Response: Yes, that is correct. Data was split into a calibration (80%) and independent validation (20%). And then the tenfold cross-validation, repeated 5 times, was applied on the calibration subset. We have reformulated for better clarity. Manuscript lines (see lines 224 – 231): The RF models built on data covering the whole area of Sweden are hereafter called "global models". The RF models created for each of the subareas are hereafter reported as "local models". Considering the subareas as strata, the local models were built by randomly splitting the local datasets into calibration (80%) and validation (20%) subset. The training set of the global models was constituted by merging the 80% split of the strata dataset. To avoid comparison bias, both the global and local models were evaluated on the same validation subset. Consequently, each global model was evaluated again three validation set separately corresponding each to the 20% split of the Northern, Central and Southern local dataset. The merged 20% split of these local datasets was then used as validation set at national scale. We trained both global and local models on the calibration subset using tenfold cross validation with 5 repetitions using the R "caret" package (Kuhn, 2015). L276-285: Here, the results for the independent validation are a bit short compared with the report for the cross-validation, or if you refer to the independent validation as "local models after cross validation" (L282), maybe that it not very clear. I was looking at Table 4 and the numbers don't seem to correspond completely. Please revise this (e.g., R2 for allV at independent validation 12-36 % and 17-32 % at cross-validation). - Author's Response: We have now modified Table 4 which presents only the cross-validation results of the local models. This because the error metrics of these local independent validations were somehow repeated in Figure 2. Thanks for notifying about the numbers which are now corrected for the cross-validation results in Table 4. Manuscript lines (see lines 283 - 284): The variances explained by the local models based on cross validation varied from 17% to 32% for allC models, 12% to 25% for the SSC models and from 5% to 20% for the GoC models. L292-293: This sentence is not completely clear. Please specify that the local models had better performance than the global models in term of RMSE within each set of variables. - Author′s Response: Sentence corrected. Manuscript lines (see lines 296 – 297): For the humus layer (Fig. 2A), the mineral (Fig. 2B) and total soil layers (Fig. 2C), the local models had in general better performance than the global models in term of RMSE within each set of variables. L360-362: Could you provide the map of standard deviation? - Author′s Response: We have computed the percentage of the ratio standard deviation/mean SOC stock prediction (coefficient of variation) to express the uncertainties for easy interpretation. Manuscript : see Figure 6 L491-495: The relevance of soil texture as predictor of SOC stock is also explained by the physico-chemical SOC stabilization mechanisms. Clay minerals and clay and silt sized particles generally have a positive correlation with mineral SOC stocks, as the association of organic matter with mineral surfaces, and occlusion inside aggregates hinders microbial decomposition and enhances SOC accumulation. There are many references in the literature on this topic. For example: Lützow, M.V., KögelâĂŘKnabner, I., Ekschmitt, K., Matzner, E., Guggenberger, G., Marschner, B. and Flessa, H., 2006. Stabilization of organic matter in temperate soils: mechanisms and their relevance under different soil conditions–a review. European journal of soil science, 57(4), pp.426-445. - Author′s Response: Thanks for pointing out the role of physicochemical mechanisms in the stabilization of SOC. We have agreed with this argument and this aspect has now been taken into account in our discussion as pointed out in this comment. Manuscript lines (see lines 503 – 507): On the other hand, the relevance of soil texture as predictor of SOC could be related to the physicochemical SOC stabilization mechanisms. Clay minerals as well as clay and silt sized particles generally have a positive correlation with mineral SOC stocks, as the association of organic matter with mineral surfaces, and occlusion inside aggregates hinders microbial decomposition and enhances SOC accumulation (Lützow et al., 2006; Zhang et al., 2020).

L550-554 & 559: Consider my comment on how there would be error propagation and the final uncertainty of the SOC predictions may be increased when maps of these site attributes are included as predictors for mapping. However, I would also include

these maps as predictor variables when they are available. - Author′s Response: We indeed agree with the fact that predictions with the maps of the site specific variables will involve additional uncertainties in final maps and prediction accuracy will drop as compared to our current approach which focused only on the observation data. Our interpretation failed to put this clearly into perspective and we have now created a section discussing this issue. To elaborate more on this issue in that section, we made some preliminary maps (which need further improvements because of low kappa values) of the site specific variables using Random Forest and additional dataset from the inventory data. These maps (SI-11) were then used as covariates to predict SOC stock (SI-12). Manuscript lines (see lines 585 – 615): see section 4.4 Implication and limitations of the study DSM relies on existing maps for building regression models and ultimately prediction for mapping. The quality and accuracy of predictions depend as discussed earlier on choosing the most relevant covariates in relation to the target to be predicted. The present study revealed that covariates which were available as maps did contribute to the MDA, but site characteristics were more prominent in relation to the SOC stock in Sweden. This might suggest that mapping these variables that were more decisive for SOC stock prediction and including them as covariates for mapping may improve accuracy. Since the primary focus of the present study was mainly to evaluate the GoC data versus the SSC data at different scale of modelling and not primarily for making a map, the observed data of the latter were used. However, since only the observed data of the site characteristics were considered, this study fails to consider that the mapping of these site characteristics would involve modelling errors and the propagation of these errors into the final maps of these site variables might actually reduce their predictive power. For completeness, we carried out a preliminary mapping of the site characteristics (SI-11) using additional soil inventory data, random forest and the GoC as predictors. These mapped site characteristics (mSSC) were then used as covariate for predicting the SOC stocks.

Table 6 presents the error metrics after independent validation for both local and global models along with the percentage margin of the RMSE in relation of the models based on GoC. First, the local mSSC based models still recorded lower RMSE as compared to global mSSC models. Compared to the GoC models, the overall positive percentage margin of the RMSE for the independent validations indicated that the mSSC models recorded the lowest RMSE. However, when assessing the RMSE margin between the global models of GoC and SSC, negative percentages were mainly recorded for the Northern Sweden independently of the depth. This indicated that the mSSC based global models were less accurate at predicting SOC stock locally in the Northern Sweden while the mSSC based local model did present a better prediction for Northern Sweden for the humus layer and mineral SOC stock. The mean SOC predictions based on the mSSC showed a stronger increasing gradient from Northern to Southern Sweden (SI-12) as compared to the pattern observed with the GoC maps. However, the uncertainty distribution was of similar magnitude (SI-12) as those observed for the maps based on GoC probably due to error propagations as these covariates were used to make the site specific characteristics maps. This suggests that the SSC should still be supplemented for improvement at this stage with other covariates different from the GoC such as multi-temporal spectral (e.g. normalized difference vegetation index) data that are able to capture vegetation dynamic in forests. Notwithstanding the fact that was obviously error propagation, the study of which was beyond the scope of this study, the preceding results tend to confirm the potential of the high resolution maps of the site characteristics to contribute to the improvement of SOC stock prediction as compared to using only the GoC data. Given that the preliminary mappings of the SSC recorded low kappa (0.17 – 0.48) values (SI-11) at this stage further improvements are still necessary to improve their predictive ability and associated coefficient of variations.

Technical comments L20: “Random Forest models”. - Author′s Response: Correction made. Manuscript lines (see line 20): We use the Swedish National Forest Soil Inventory (NFSI) database and a digital soil mapping approach to evaluate the prediction performance using Random Forest models calibrated locally for the northern, central and southern Sweden (local models) and for the whole Sweden (global model).

L43: Place the abbreviation of carbon (C) before in the text, in line 35 when you use it for the first time. - Author′s Response: Correction made. Manuscript lines (see lines 35): About 30 % of the global terrestrial carbon (C) stock is stored in forests with 60 % located below ground (Pan et al., 2011)….(see line 43) In that context, analysis of the C cycle in forests is central to understanding management and climate-induced changes in global C pool. L228: “built”. - Author′s Response: This section of the manuscript was changed and rephrased L294: “best local models”. - Author′s Response: Correction made. Manuscript lines (see lines 297 - 298): The best local models were mostly associated with all covariates or site specific covariates especially for central and southern Sweden L326: 40K (capitalize the K). - Author′s Response: Correction made. Manuscript lines (see lines 333): A similar trend is observed in northern Sweden while the remaining models recorded 40K as second key variable in addition to soil moisture and soil type for the central and southern Sweden respectively. L372: “When predictions were carried out”. - Author′s Response: Correction made. Manuscript lines (see lines 378): When predictions were carried out on the same validation set, local models including those of southern Sweden generally outperformed the global models L385: “outperform” - Author′s Response: Correction made. Manuscript lines (see lines 393 – 394): For example, local models in central Sweden required all covariates to outperform global models for the humus layer, mineral soil and total SOC stock. L386-387: Please indicate that you refer to the best local models. - Author′s Response: Correction made. Manuscript lines (see lines 394 – 396): The same pattern was observed for Southern Sweden except for the mineral SOC stock for which the best local model was associated with the SSC. The local best model for the total SOC stock in Northern Sweden was also associated with SSC. L397: “remained low” - Author′s Response: Correction made. Manuscript lines (see lines 406 - 408): However, despite the combination of these two category of covariates, the accuracy of the SOC stock prediction remained low for both the global models… L475: “organic matter” - Author′s Response: Correction made. Manuscript lines (see lines 482 - 483): This makes them less relevant in contrast to SSC taken at plot level which describe more closely factors controlling the decomposition and stabilization of organic matter. Figure 6: Please, indicate in the caption which in the figure (left/right) are the global and the local models. Also, maybe you could include a figure with the standard deviation or the 5th and 95th percentiles (predicted with the quantile random forests regression) so we can also visualize the uncertainty. The colour scale for the total SOC stock (in less extent) but mainly for the mineral SOC stock is not very clear, as there are different tonalities of green and brown for different value ranges. Could you use a different sequential palette, like for the predictions of the humus layer? (maybe multi-hue sequential palette). For example, the package colorspace has many options. - Author′s Response: Thanks for the comments. We have used another color scale for the figure 6 of the mineral soil SOC stock. We have computed the percentage of the ratio standard deviation/mean SOC stock prediction to express the uncertainties for easy interpretation. Supplementary material S1: Maybe you can expand the supplementary material one more page and make the plots larger on their y axis. They are not very clear like this. - Author′s Response: We have taken this into account by adding two more page to make the plots bigger. When you map over the whole study area, what GIS layer did you use to mask non-forested areas? you could include that in the methods. - Author′s Response: Thanks for the inquiry. We use only the forest dataset and subsequent results only refer to forested areas. However, the maps in figure 6 was extrapolated for the whole country not excluding non-forested areas because any use of these maps will only be related to forested areas.

Please also note the supplement to this comment:
https://soil.copernicus.org/preprints/soil-2020-75/soil-2020-75-AC3-supplement.pdf

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Interactive comment on SOIL Discuss., https://doi.org/10.5194/soil-2020-75, 2020.