Author response: Interactive comment on “Scaling impacts on environmental controls and spatial heterogeneity of soil organic carbon stocks” by U. Mishra and W. J. Riley

Anonymous Referee #2

Using observational data and geostatistics approaches, this study discussed about environmental controls on soil organic carbon (SOC) stocks and spatial heterogeneity of SOC stocks at different spatial (sample) scale. The authors shows that 1) different environmental predictors of soil organic carbon (SOC) stocks at different spatial scales; and 2) the variance of predicted SOC stocks decreased with spatial scale over the range of 50 to ~500 m, and remained constant beyond 500 m scale. The conclusions make sense and are expected. The manuscript is well organized and well written. But before its publication in Biogeosciences, several concerns should be addressed.
Response – We thank the reviewer for summarizing our results and indicating limitations of our study. In the revised manuscript, we have adopted all the changes recommended by the reviewer and used the last paragraph of the discussions section to discuss limitations of our study as suggested.

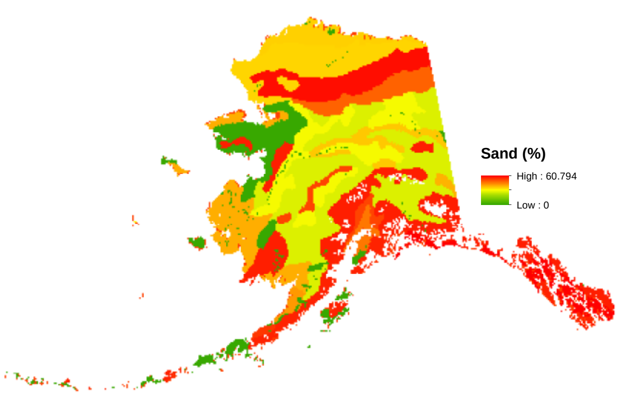
1. This study only used data from Alaska, if using observational data from larger spatial range such as boreal to tropical (as normal scale ESMs works), the dominant predictors of SOC may be different as the results from Alaska even at the same scale such as 50 m. In the discussion, the authors should leave some space for larger scale. For example, if more samples were taken from whole USA, applying the same methods used in this study, the conclusions in this study are still the same?
Response – Thanks for this suggestion. We agree with the reviewer, that the results might differ in absolute magnitude of the regression coefficients of environmental factors if a global or continental scale study would have been conducted, as both the spatial heterogeneity and environmental controls of SOC stocks are determined by the variability of soil-forming factors. We believe that the overall scaling impacts on environmental controllers and spatial heterogeneity might remain the same. However, conducting such a large scale study at high spatial resolution as in this study is not within the scope of our current efforts. And as suggested by the reviewer, we have added text in the discussion section to add limitations of our study (P19L19-23).

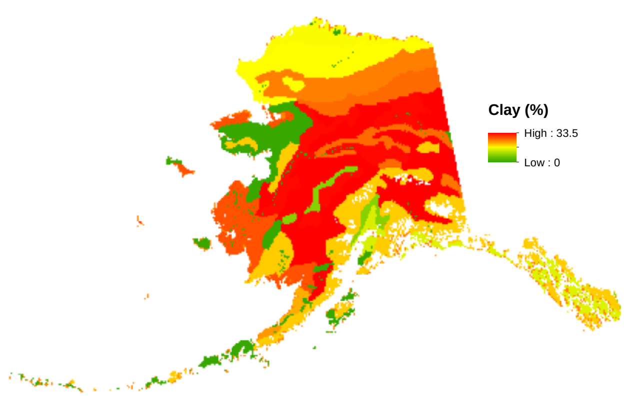
2. Page 1730, line 7, how about the auto-correlation between independent variables for predicting SOC stocks? Does the auto-correlation impact the coefficients (beta) for each predictor (as shown in Figure 3)?
Response – We thank the reviewer for this question. We paid careful attention about auto-correlation between independent variables (multicollinearity) while selecting log linear model predictors (Mishra and Riley, 2012; 2014). During the selection of environmental predictors we chose uncorrelated environmental variables (P1730L2-3). This was done by calculating the variance influence factors (VIFs) for each of the selected variables. The VIFs for all the variables included in models selected at different spatial resolutions were <5. High levels of

multicollinearity (VIF > 10) can falsely inflate the least squares estimates (Kutner et al., 2004; O'Brien R., 2007; Gomez et al., 2013); therefore only variables with lower VIF values were used in our study. Therefore, multicollinearity between selected environmental variables was not a problem in the selected models at different spatial resolutions. We added text to further clarify our method of model selection (P11L8-12).

3. Page 1733, Line 6-13, it seems arbitrary to set the 25% as criteria of spatial dependency. It is really large difference between 27% at 50 m and 100 m scales and ~20% at other scales?
Response –We agree with the reviewer that the difference between 27% and ~20% is not large. However, we did not set this criterion of spatial dependency, but have used a criterion that is well documented and well cited in literature (Cambardella et al., 1994; Karvchenko, 2003; Sun et al., 2003; Mora-Vallejo et al., 2008) to characterize and describe the spatial dependency of soil properties including SOC stocks. This criteria basically relies on the geostatistical theory which assumes that as the nugget increases the spatial structure of an environmental variable decreases.

4. Page 1734, Line 22-26, how about soil texture controls on SOC in this study? Is it possible to show whether silt/clay fraction is a significant predictor on SOC, and at which scale?
Response – We made a strong effort to address the specific reviewer concern that we investigate the use of soil texture in scaling of SOC stocks. The soil properties at a particular location were predicted using soil forming factors (P1724, L1-4) (Jenny et al., 1941; McBratney et al., 2003). In practice, ancillary information of soil forming factors that are extensively available over the study area was used for spatial prediction of different soil properties. Soil texture does impact the SOC stock at a location. However, to our knowledge, soil texture information at fine resolution representative of natural landscapes does not exist. We used the soil texture data that is currently used in CLM 4.5 (Bonan et al., 2002), which was available at ~8 km (7559.1m) spatial resolution across Alaska. However, these data show one soil texture value for each ecoregions of Alaska (see figures below). This implies that although the data has a spatial resolution of ~ 8 km, it this must have been derived from a source with a much coarser spatial resolution (International Geosphere-Biosphere Programme soil dataset that had 4931 soil mapping units globally; CLM 4.5 Technical notes). Because of this limitation, we were unable to include soil texture in the current scaling study. However, if soil texture information becomes available at fine resolution in the future, this information could be readily integrated using the methods we describe here. We have modified the text in the Discussion section to address this issue (P20L4-13).





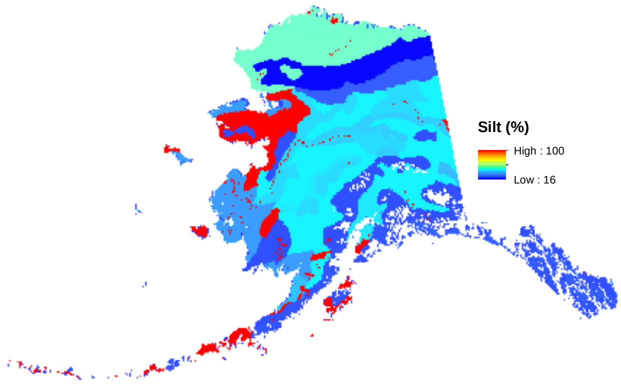


Figure: Soil texture data currently available for State of Alaska in CLM4.5 (Bonan et al., 2002)

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