

Interactive comment on “Comparison of spatial association approaches for landscape mapping of soil organic carbon stocks” by B. A. Miller et al.

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We thank the reviewer for their comments, which we have used to clarify the research strategy and generally improve the manuscript.

Comment-1: Samples are taken in clusters covering only 12 fields in the study area (containing presumably a few 102 fields), with rather a poor spatial distribution. This will most probably affect the distribution of the data in the multi-dimensional space, and hence, do not cover enough the associated landscape complexity within the study area. These 2 concerns (poor spatial distribution and poor distribution in multi-dimensional space) are a major problem when the model is used for extrapolation / predicting pixels elsewhere in study area, i.e. outside the variable range covered by the calibration

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dataset.

Response-1: Although the samples are grouped spatially in fields for logistical reasons, they were carefully located to capture the distribution of conditions across the feature space of the agricultural fields. Specifically, the samples include the variety of parent materials in the study area, form transects across topographic positions, as well as cover regional highs and lows. If the modelling technique relied on spatial autocorrelation, such as with kriging, the spatial position of these samples would indeed have been a problem. However, because the modelling method uses spatial regression, which relies on the principle of spatial association, the important space to cover was the feature space. Therefore, the samples were taken to encompass the variable range of the agriculture fields as best could be determined prior to sampling. Notably, only agricultural fields were sampled and thus non-agricultural areas are masked out of prediction maps because they were outside the variable range covered by the calibration dataset. Text has been added to emphasize these points.

Comment-2: As a consequence, it's quite possible that the differences in SOC stock maps between the two methods are more the consequence of the fact that the 2 modelling approaches (i.e. direct versus indirect) are reacting differently on this shortcoming (inappropriate multidimensional data cover) then it is actually reflecting a real difference in model output just/purely caused by the fact that 2 different approaches were used.

Response-2: We understand this concern, but consider the variables used to calculate the SOC stock (indirect) and the SOC stock itself (direct) to be intertwined due to their definitional relationship. Because of this relationship, covering the feature space of one approach increases the probability that the feature space of the other approach is also covered.

Comment-3: Finally, it's clear how the authors calculated errors on SOC stocks by using classical error propagation techniques for individual pixels (i.e. for both the di-

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rect and the indirect method (including error predictions on components)), but it's not clear if/how spatial autocorrelation was taken into account when mapping these errors. It's important to integrate this effect of spatial autocorrelation in order to make a fair comparison between the error maps obtained by the two methods.

Response-3: Spatial autocorrelation was used in the grouping of rule condition zones, on which error estimations are applied. Spatial autocorrelation minimizes how different unsampled areas within a condition zone could be from the sampled locations. This closely resembles the approaches of Shrestha and Solomatine (2006) and Malone et al. (2006) for taking autocorrelation into account when mapping estimated errors from spatial regression models.

Interactive comment on SOIL Discuss., 1, 757, 2014.