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Letter to the editor

Paired resampling to detect field-level soil organic carbon stock change. Comment on "Testing the feasibility of quantifying change in agricultural soil carbon stocks through empirical sampling" by Bradford et al.

Bradford et al. (2023) highlighted how spatial variability of SOC stocks is a major obstacle for detecting single-field SOC stock changes when using field sampling schemes common in measurement, reporting, and verification (MRV) protocols. Specifically, when soil sampling is constrained to economically feasible densities (e.g., ~1 sample ha^{-1}), and spatial sampling locations are randomly selected through time, Bradford et al. (2023) showed that single-field estimates of SOC stock change can be highly inaccurate. While sampling density often is limited by logistical and financial constraints, the decision to employ a temporally random versus a paired sampling scheme (i.e., temporal resampling near the original sampling locations) should pose minimal constraints (e.g., it may require a GPS receiver). Bradford et al. (2023) suggested that a paired design theoretically could improve SOC stock change estimates over temporal random sampling and that more research exploring this approach should be undertaken. While we agree that this issue is urgent given a lack of consistency in currently employed MRV protocol sampling schemes (Oldfield et al., 2021), several studies have shown the statistical benefits of paired temporal sampling for estimating temporal changes in soil properties (e.g., Papritz and Webster, 1995; Lark, 2009; Brus and de Gruijter, 2013). Combining an approach analogous to Bradford et al. (2023), a spatially gridded SOC stock dataset, and a spatial autocorrelation model, we visually demonstrate how resampling soils near the original sampling locations mitigates sampling errors associated with temporal random sampling when estimating SOC stock change.

We used a historical dataset from the Wisconsin Integrated Cropping Systems Trial (WICST), a long-term agroecosystem experiment located on Mollisols in south-central Wisconsin (Posner et al., 1995). In 1989, soil samples for SOC mass fraction and bulk density were collected at 0 to 15- and 15 to 30-cm increments at alternating points on a 27.5 × 27.5-m grid across a ~22-ha field (Sanford et al., 2012). We interpolated this dataset with ordinary kriging and an exponential isotropic spatial autocorrelation model using *ggstat* (Gräler et al., 2016) to produce a 1 × 1-m grid of 0 to 30-cm SOC stocks (Fig. 1A). In line with the approach used by Bradford et al. (2023), we divided a 16-ha portion of the field into 4-ha subfields to serve as discrete sampling units (Fig. 1A). We simulated four sampling scheme scenarios, where each consisted of two hypothetical time points (time 1 and time 2) with no true temporal change in the SOC stock at any location in the field. In the first scenario, soil samples were selected at random locations at both time points (Fig. 1B) analogous to Bradford et al. (2023). In the last three scenarios, soil samples for the first time point were selected randomly, and samples for time 2 were selected in a random direction at 50, 25, or 10-m distances from each of the time 1 locations, while remaining within the original 4-ha subfield (Fig. 1C, 1D, 1E). In all scenarios, samples were collected at a density of 1 sample ha^{-1}, samples were evenly distributed among the 4-ha subfields, and each scenario was simulated 100 times. All data processing and simulation was conducted in R 4.2.3 (R Core Team, 2023). We refer to the difference between field-average SOC stocks between the two simulated time points (time 2 – time 1) as "apparent SOC change," because the true SOC change was zero, and therefore any observed difference between the time points is artifactual.

When soil sampling locations were randomly selected at both time points, our simulations confirmed those of Bradford et al. (2023), with relatively high dispersion in apparent SOC change estimates (2.3 Mg ha^{-1} median absolute deviation, MAD) among simulations and a prominent regression to the mean (Fig. 2A). When resampling at time 2 was constrained to locations 50 m from the time 1 sampling locations, the dispersion of apparent SOC change was similar to random sampling (2.4 Mg ha^{-1} MAD), but the magnitude of regression to the mean was reduced (Fig. 2B). When resampling locations were constrained to within 25 m of the original sampling point, dispersion of apparent SOC change decreased (1.3 Mg ha^{-1} MAD) and regression to the mean was reduced (Fig. 2C). In the final scenario where resampling at time 2 was constrained to 10 m from the time 1 locations, the dispersion of apparent SOC change was further reduced (0.7 Mg ha^{-1} MAD) and the regression to the mean was not evident (Fig. 2D). Given that SOC stocks generally show strong field-scale spatial autocorrelation (Gamble et al., 2017), we expect that paired temporal sampling schemes will generally improve estimates in SOC stock change in single fields where sampling density is constrained (e.g., Papritz and Webster, 1995; Lark, 2009).

Our *in silico* simulation is limited, as our soil samples were collected at distances >25 m apart, and therefore the spatial variability and correlation structure of SOC stocks at smaller spatial scales at our site are not well resolved. Recent work by Poeplau et al. (2022) reported significant unstructured spatial variability at scales <20 m suggesting that it may be necessary to collect replicate soil samples at each location (e.g., three soil cores within 1 m at each time point) to improve overall accuracy of SOC change measurements using a paired approach. Presumably, these replicate samples could be composited prior to laboratory analysis but would nonetheless incur additional sampling costs. An additional limitation is that the paired approach does not provide improvements over the random approach for estimating the initial mean SOC stock, which has implications for estimating changes in the SOC stock if the SOC stock change depends on the initial SOC stock (Lark 2009). For example, if true SOC stock changes are greater in locations

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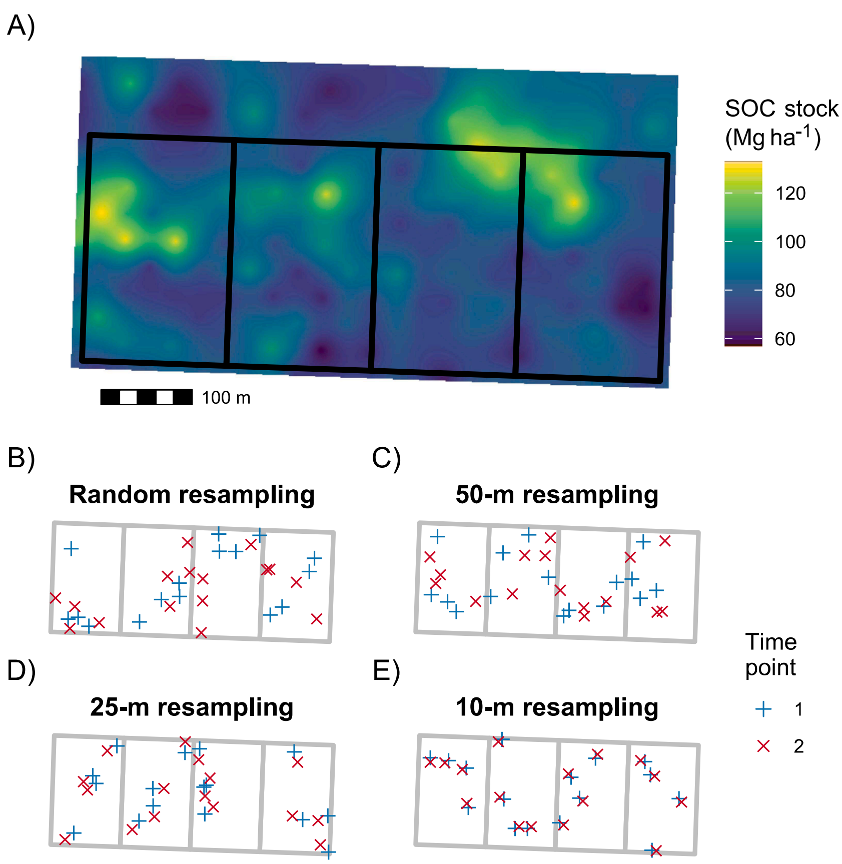

Fig. 1. Spatial variability of soil organic carbon (SOC) stocks (0 – 30 cm) at the Wisconsin Integrated Cropping Systems Trial (WICST) as interpolated from gridded samples using a spatial autocorrelation model (A). The overlaid outline shows the 16-ha field and 4-ha subfields that were used for the sample scheme simulations. Example instances of sampling schemes where soil samples are collected at two time points (time 1 or time 2) using a temporally random sampling approach at both time points (B) versus paired approaches where samples at time 2 are collected in a random direction at 50-m (C), 25-m (D), or 10-m (E) distances from the time 1 samples.

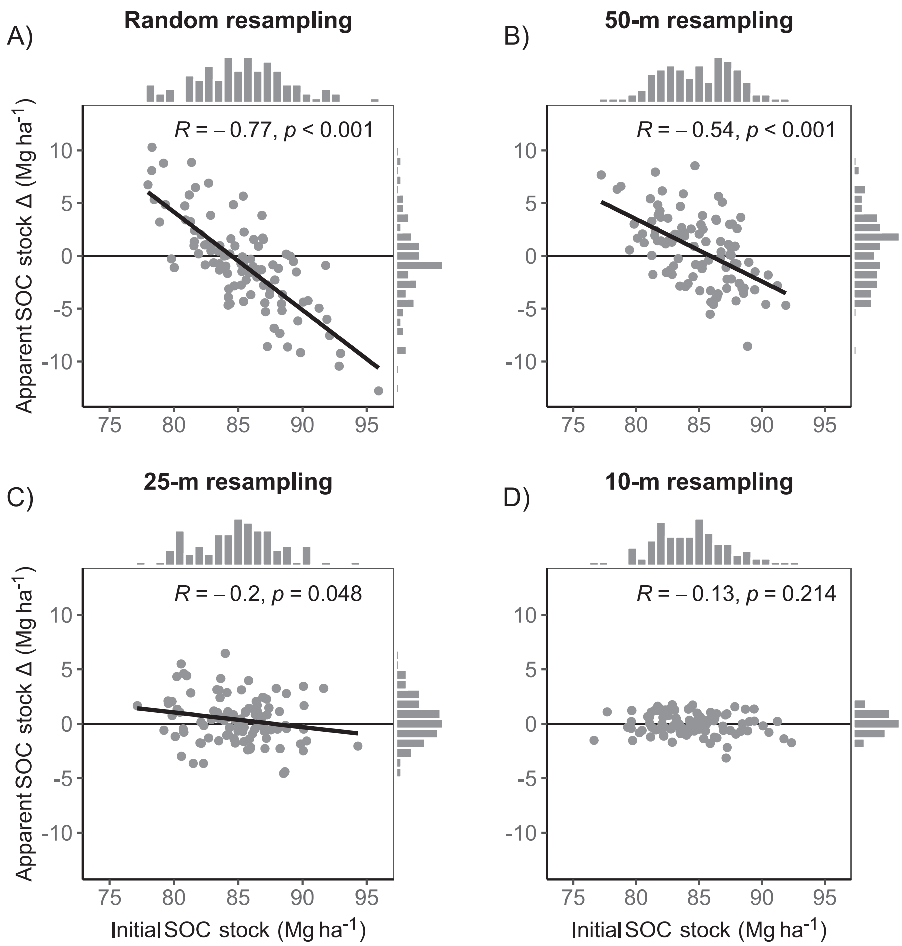

Fig. 2. Results from soil sampling scheme simulations showing the field-average 0 – 30 cm initial soil organic carbon (SOC) stock (time 1) versus the field-average apparent SOC stock change (time 2 – time 1), with histogram distributions shown on the graph edges. Simulations used a temporally random sampling scheme (A) or sampling schemes where time 2 samples were collected at locations 50-m (B), 25-m (C), or 10-m (D) away from the time 1 locations. All scenarios were simulated 100 times, and in each case the true SOC stock change was zero. Pearson correlation coefficients and respective p-values are shown to diagnose regression to the mean.

with higher initial SOC stocks than locations with lower initial SOC stocks, and if the initial SOC stock is overestimated due to random sampling error, then changes in SOC stocks likely will be overestimated as well. To mitigate this issue, initial sampling locations can be selected using a stratified random design, where strata are assigned by soil classification, topographic wetness index, or other likely SOC covariates (Potash et al., 2022).

The optimal sampling design for an SOC stock monitoring project may be different than that of an SOC stock inventorying or mapping project (Lark 2009; de Gruijter et al. 2016). That is, compared to the temporal random approach, the temporal paired approach provides a better estimate of the SOC stock change but provides a less robust estimate of the mean SOC stock (e.g., Brus and de Gruijter, 2013). If both the mean SOC stock and SOC stock change estimates are desired, hybrid sampling methods such as serially alternating or supplemented panel approaches may be more prudent (Brus and de Gruijter, 2013). In cases where soil at the paired sampling locations could be fraudulently manipulated between campaigns, optimized new resampling locations could be determined based on the measurements from the previous campaign (de Gruijter et al. 2016). However, for routine SOC stock monitoring projects, where the SOC stock change is the variable of interest and the risk of fraudulent soil manipulation is negligible, paired temporal sampling is likely the most practical option.

We concur with Bradford et al. (2023) that field-level SOC work is a necessary step forward towards improving our estimates of SOC stock changes under working-farm conditions across the landscape, which cannot be attained from plot-level experiments. In our on-farm work, and in other discussions with land managers, we find that many individuals have a genuine desire to quantify SOC stock changes under their management practices for both personal and market validation reasons. Thus, in addition to addressing the scientific and economic needs to quantify field- and landscape-level SOC changes, on-farm SOC work provides a meaningful connection between land managers, their communities, and broader soil and climate goals. As such, there is an urgent need to accurately quantify field-level SOC stock changes at economically viable soil sampling densities. We hope that future multiscale empirical studies will be undertaken to continue to improve the protocols for assessing SOC stock changes at the field-level. In the meantime, we suggest that MRVs place a greater emphasis on temporally paired sampling schemes, which will likely provide more robust estimates of field-level SOC change.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

Bradford, M.A., Eash, L., Polussa, A., Jevon, F.V., Kuebbing, S.E., Hammac, W.A., Rosenzweig, S., Oldfield, E.E., 2023. Testing the feasibility of quantifying change in agricultural soil carbon stocks through empirical sampling. Geoderma 440, 116719. https://doi.org/10.1016/j.geoderma.2023.116719.

Brus, D.J., de Gruijter, J.J., 2013. Effects of spatial pattern persistence on the performance of sampling designs for regional trend monitoring analyzed by simulation of space-time fields. Comput. Geosci. 61, 175–183. https://doi.org/10.1016/j.cageo.2013.09.001.

de Gruijter, J.J., McBratney, A.B., Minasny, B., Wheeler, I., Malone, B.P., Stockmann, U., 2016. Farm-scale soil carbon auditing. Geoderma 265, 120–130. https://doi.org/10.1016/j.geoderma.2015.11.010.

Gamble, J.D., Feyereisen, G.W., Papiernik, S.K., Wente, C., Baker, J., 2017. Regression-kriged soil organic carbon stock changes in manured corn silage–alfalfa production systems. Soil Sci. Soc. Am. J. 81, 1557–1566. https://doi.org/10.2136/sssaj2017.04.0138.

Gräler, B., Pebesma, E., Heuvelink, G., 2016. Spatio-Temporal Interpolation using gstat. The R Journal 8, 204–218. https://doi.org/10.32614/RJ-2016-014.

Lark, R.M., 2009. Estimating the regional mean status and change of soil properties: two distinct objectives for soil survey. Eur. J. Soil Sci. 60, 748–756. https://doi.org/10.1111/j.1365-2389.2009.01156.x.

Oldfield, E.E., Eagle, A.J., Rubin, R.L., Rudek, J., Sanderman, J., Gordon, D.R., 2021. Agricultural soil carbon credits: Making sense of protocols for carbon sequestration and net greenhouse gas removals. Environmental Defense Fund, New York, New York. http://www.edf.org/sites/default/files/content/agricultural-soil-carbon-credits-protocol-synthesis.pdf.

Papritz, A., Webster, R., 1995. Estimating temporal change in soil monitoring: II. sampling from simulated fields. Eur. J. Soil Sci. 46, 13–27. https://doi.org/10.1111/j.1365-2389.1995.tb01809.x.

Poeplau, C., Prietz, R., Don, A., 2022. Plot-scale variability of organic carbon in temperate agricultural soils—Implications for soil monitoring. J. Plant Nutr. Soil Sci. 185, 403–416. https://doi.org/10.1002/jpln.202100393.

Posner, J.L., Casler, M.D., Baldock, J.O., 1995. The Wisconsin integrated cropping systems trial: combining agroecology with production agronomy. Am. J. Altern. Agric. 10, 98–107. https://doi.org/10.1017/S0889189300006238.

Potash, E., Guan, K., Margenot, A., Lee, D., DeLucia, E., Wang, S., Jang, C., 2022. How to estimate soil organic carbon stocks of agricultural fields? perspectives using ex-ante evaluation. Geoderma 411, 115693. https://doi.org/10.1016/j.geoderma.2021.115693.

R Core Team, 2023. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. https://www.r-project.org/.

Sanford, G.R., Posner, J.L., Jackson, R.D., Kucharik, C.J., Hedtcke, J.L., Lin, T.-L., 2012. Soil carbon lost from Mollisols of the North Central U.S.A. with 20 years of agricultural best management practices. Agr. Ecosyst. Environ. 162, 68–76. https://doi.org/10.1016/j.agee.2012.08.011.

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