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RESEARCH ARTICLE

Plot-scale variability of organic carbon in temperate agricultural soils—Implications for soil monitoring#

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Abstract

Background: Detecting changes in soil organic carbon (SOC) stock requires systematic and random sampling errors to be kept to a minimum. Especially in soil monitoring schemes based on soil profiles pits, it is important to understand if a minimum spatial shift of that profile pit during resampling could render resampling errors caused by spatial variability negligible.

Aims: We aimed at (1) quantifying the random SOC stock error caused by a minimum shift in sampling location of one profile and (2) assessing whether an increase in the number of profile pits to three could significantly decrease the resampling error caused by spatial variability of the relevant parameters.

Methods: Eight croplands and grasslands in northeast Germany were sampled. Three sampling designs were compared: one profile resampled (1) by one, (2) by three profiles or (3) three profiles resampled by three. In addition, 16 soil cores were taken per site to characterise overall plot-scale heterogeneity and assess general patterns of spatial dependence of relevant parameters.

Results: Spatial dependence of all assessed parameters was weak. Accordingly, the resampling of one profile by one induced a high mean absolute error of 5.1 and 7.6 Mg C ha^{-1} at a 0–30 cm depth for croplands and grasslands (7.5% and 8.5%). This error was reduced by approximately 50% when three profiles were resampled by three profiles.

Conclusions: Even with the smallest spatial shifts possible, monitoring of SOC stocks relies on replicated resampling to detect management or climate change-induced trends in reasonable and relevant timescales.

KEYWORDS
bulk density, sampling error, short-distance variability, soil carbon, soil survey

1 | INTRODUCTION

The positive role of soil organic carbon (SOC) in soil health, fertility and as a potential sink of CO_2 is widely acknowledged (Minasny et al., 2017; Smith et al., 2019). There are monitoring initiatives on various scales all over the globe to establish solid baselines and evaluate SOC stock changes over time (van Wesemael et al., 2011). In addition to national or international inventories and monitoring programmes that are usually run by government institutions, changes in SOC are also assessed in a number of other contexts, including long-term experiments and emerging carbon credit schemes. From plot to continental scale, the dilemma faced is that SOC stock changes over time are usually small compared with the overall size of the pool and its natural spatial heterogeneity. Therefore, detecting changes in SOC stocks in timescales relevant for the abovementioned activities presents a major challenge (Goidts et al., 2009; Smith, 2004).

For national soil inventories, a time interval of about 10 years is suggested as a minimum to detect changes in SOC stocks on a country scale (Saby et al., 2008; Schrumpf et al., 2011). Based on measured topsoil SOC variances and sample numbers, Saby et al. (2008) estimate that European countries would require between 3 and >70 years to be able to detect SOC stock changes. The minimum detectable difference (MDD) between SOC stock measurements decreases with sample size, thus national or continental inventories with a sufficiently dense grid of sampling sites are more likely to capture average trends in SOC over time. Indeed, several repeated national inventories in European countries have succeeded at detecting significant SOC stock or content changes on a country scale (Bellamy et al., 2005; Heikkinen et al., 2013; Poeplau et al., 2015).

Soil inventories have the potential to reveal more than average temporal trends in soil parameters or indicators: when sufficient background information is available for each sampling site, such as current agricultural management, land-use history or pedoclimatic conditions, observed changes in soil parameters could potentially be directly linked to these drivers (Mayer et al., 2019). Such direct links have the potential to quantify management effects on SOC dynamics, understand observed trends and their regional patterns, and thus facilitate agricultural policy-making. Especially for such direct links, an accurate relocation and resampling of soils at a certain interval of time is necessary and considered to be the most effective approach in soil monitoring schemes (Lark et al., 2006; Mol et al., 1998). However, even if the exact sampling point can be relocated for resampling, soil that has been sampled once has been disrupted and cannot be directly resampled. Therefore, the correlation between different sampling dates in national inventories often reveals a huge scatter, which can mostly be explained by large plot-scale variability causing random deviations between two sampling events (Heikkinen et al., 2013). Such noise hampers in-depth analyses of the causes of SOC change and should be avoided by minimising the different causes of random errors in SOC stock estimates (Goidts et al., 2009). In essence, soil monitoring systems have to deal with spatiotemporal variability for estimating population means and their changes over time (Lark et al., 2006; Papritz & Webster, 1995a, 1995b). Determination of the latter requires to keep the resampling error at the sampling plot scale during resampling at a minimum, which is why pairing sampling positions at two successive sampling events is recommended (Papritz & Webster, 1995a, 1995b).

In practice, time and money are always limiting factors. Optimised, knowledge-based sampling strategies are thus crucial to save those resources and successfully verify changes in SOC stocks (Lark et al., 2006; Smith, 2004). However, there has been minimal quantification of plot-scale heterogeneity, especially in agricultural soils, hampering the design of robust, cost-effective and time-effective sampling schemes that enable SOC stock changes to be detected and explained. Agricultural soils, particularly croplands, are often characterised by homogenised topsoils due to tillage operations, with plot-scale heterogeneity expected to be much smaller than in undisturbed ecosystems such as forests. Indeed, Conant et al. (2003) detected smaller coefficients of variation (CV) in SOC stock estimations within cropland microplots (2 × 5 m) than within forest microplots. Furthermore, Cambardella et al. (1994) found a strong spatial dependence of SOC in a cultivated soil with a lag distance of more than 100 m, while Schöning et al. (2006) found a spatial independence of samples of a forest soil after a lag distance of 5.4 m. Finally, Saby et al. (2008) found plot-scale (1–400 m^2) CV in the SOC content of European agricultural soils (3.4%) to be marginally higher than the analytical error of elemental analysis (2.5%). These examples all indicate that resampling at exactly the same location with a minimum spatial shift of the soil profile might render plot-scale variability in SOC of agricultural soils negligible, and therefore excessive numbers of individual samples per sampling site could be avoided in a national soil monitoring context.

The first German Agricultural Soil Inventory was completed in 2018. At a total of 3104 sites comprising croplands, grasslands and permanent crops, one soil profile pit was opened and sampled at fixed depth increments to a depth of 100 cm (Poeplau et al., 2020). The aim of the present study was to assess the plot-scale variability of cropland and grassland soils of differing properties to develop a resampling strategy for the abovementioned national inventory. The major questions were: (1) How large is the average resampling error in SOC stock estimation at a sampling plot caused by small-scale spatial heterogeneity, if one soil profile is resampled in direct proximity (20–60 cm apart) and (2) will the resampling error in SOC stock estimation decrease when three profiles will be sampled and resampled instead?

2 | MATERIALS AND METHODS

2.1 | Experimental design and soil sampling

A total of eight croplands and eight grasslands in north central and northeast Germany were sampled between January and May 2020. The sampling sites were selected to encompass a wide range of major soil properties (Table 1); for example, the sand content of the soils varied from 2% to 92% and SOC contents at a depth of 0–10 cm varied from 6 to 65 g kg^{-1} across the 16 selected sites. Most of the sites were located in proximity of Soil Inventory sampling sites. On the designated fields, 20 × 20 m plots were selected by keeping at least 20 m distance to obvious disturbances and boarders such as headlands, hedgerows, roads or neighbouring fields. The sites were sampled in two steps (Figure 1A). In the first step, three soil profile pits were opened to a depth of 50 cm. The first profile (P1) was located at the origin of the coordinate system (0, 0), the second (P2) 2 m to the left (−2, 0) and the third (P3) 5 m to the right (5, 0) (Figure 1A). The profile wall was always facing north. Each profile was sampled at 0–10, 10–30 and 30–50 cm using a cylindrical soil core of 250 cm^3 (height of 5 cm) to obtain undisturbed samples for soil physical parameters. Two undisturbed samples were taken vertically from the soil profile wall at each depth increment and pooled. In 0–10 cm, they were placed side by side, while in 10–30 and 30–50 cm they were stacked. To obtain disturbed composite

TABLE 1 List of sampled cropland (C1–C8) and grassland (G1–G8) sites with stage (croplands) or type (grasslands) of management, soil type (World Reference Base), average soil organic carbon (SOC) content (g kg^{-1}), fine soil density (FSD) (g cm^{-3}), rock fragments fraction (mass%), sand, silt and clay contents (mass%) and pH value in water (H_2O) at 0–10 cm depth

Site ID	Stage/type of management	Soil type	SOC	FSD	Rock fragments	Sand	Silt	Clay	pH_{H2O}
C1	Ploughed	Chernosem	18.4 ± 0.2	1.13 ± 0.05	0.1 ± 0.1	4	75	21	7.7
C2	Harvested	Gleysol	7.1 ± 0.5	1.54 ± 0.07	2.5 ± 1.3	87	9	4	6.6
C3	Cover crops	Cambisol	14.8 ± 1.0	1.21 ± 0.05	0.2 ± 0.2	14	70	16	7.1
C4	Cover crops	Gleysol	36.1 ± 2.4	1.25 ± 0.08	0	28	37	35	6.9
C5	Grubbed	Gleyic Cambisol	22.2 ± 0.7	1.32 ± 0.10	0.2 ± 0.2	80	15	5	6.2
C6	Grubbed	Gleyic Cambisol	6.1 ± 0.3	1.44 ± 0.09	3.7 ± 0.8	86	11	3	5.5
C7	Harvested	Anthrosol	10.7 ± 1.2	1.44 ± 0.09	1.9 ± 0.3	83	11	6	8.0
C8	Grubbed	Cambisol	14.7 ± 0.9	1.05 ± 0.08	4.2 ± 3.1	41	41	18	7.9
G1	Permanent green fallow	Gleysol	44.4 ± 4.6	0.80 ± 0.05	0	8	66	26	6.9
G2	Mowed pasture	Gleyic Cambisol	10.5 ± 1.9	1.27 ± 0.05	0.6 ± 0.3	92	4	4	5.3
G3	Mowed pasture	Colluvisol	64.9 ± 3.3	0.85 ± 0.04	0.1 ± 0.1	9	63	28	7.8
G4	Mowed pasture	Gleysol	64.1 ± 6.9	0.89 ± 0.06	0	3	55	42	7.2
G5	Mowed pasture	Pelosol	56.2 ± 13.6	0.94 ± 0.08	0	38	32	40	6.9
G6	Meadow	Stagnic Cambisol	53.1 ± 3.6	0.76 ± 0.07	1.2 ± 1.7	11	64	25	5.2
G7	Mowed pasture	Gleysol	41.1 ± 4.2	1.04 ± 0.07	2.6 ± 1.2	64	16	15	6.7
G8	Mowed pasture	Luvisol	27.6 ± 1.4	1.15 ± 0.05	0	2	79	19	5.9

SOC, FSD and rock fragments is the average of all analysed profile samples per site ($n = 6$ with standard deviation); all other parameters were measured in a pooled sample form the central profile (P1) with two technical replicates.

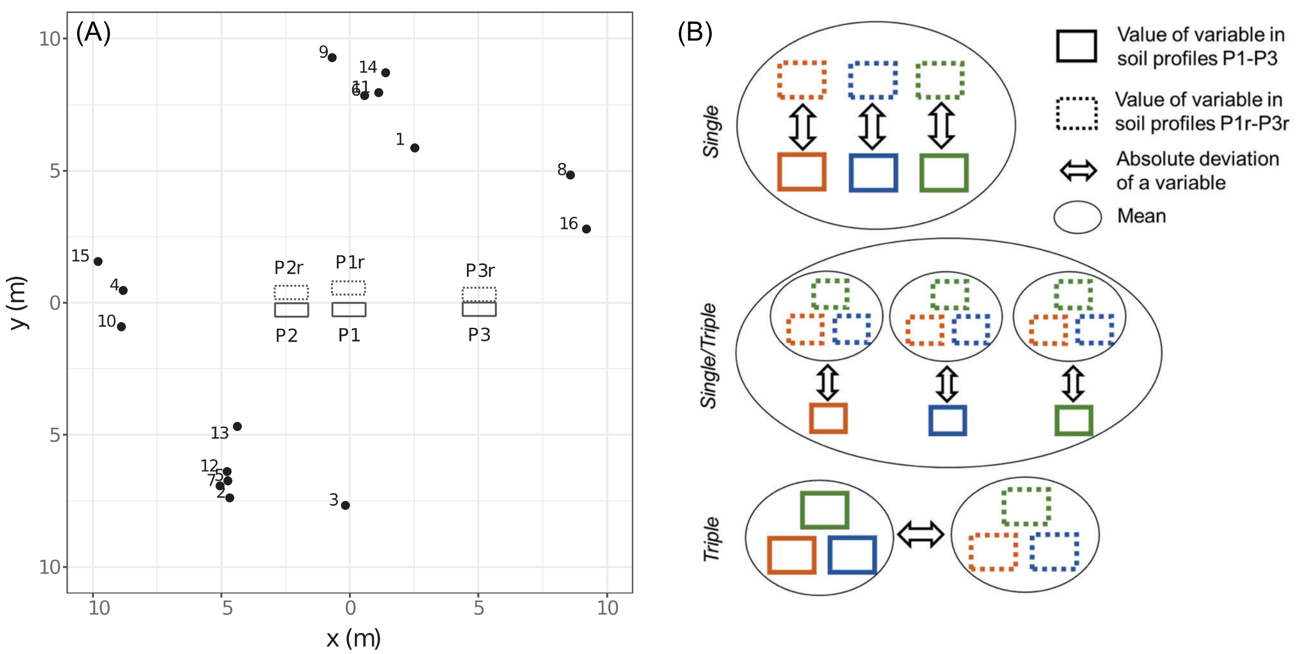

FIGURE 1 (A) Example of the sampling design with 16 randomly distributed soil core sampling points and six soil profiles with fixed positions and (B) schematic representation of how the six profiles were used to calculate resampling errors of the three sampling strategies *Single*, *Single/Triple* and *Triple*

samples for chemical analysis, a scraper was used to cut thin slices along the profile wall in the respective depth increment. After the three profiles were sampled, the profile wall was shifted by 60 cm in the case of P1, by 40 cm in the case of P2, and by 20 cm in the case of P3 to obtain profiles P1r, P2r and P3r (Figure 1A). This adjustment was made to simulate the shift during a resampling event and has to occur since identical profile walls cannot be resampled due to soil disturbance caused by initial sampling in the profile pit. The variation in shifting distance (20–60 cm) was used to additionally assess spatial dependence of SOC at the decimetre scale. The three shifted profiles were sampled in the same way as the original profiles. The soil profiles were always shifted towards north (Figure 1A), while excavated material was piled southwards.

In the second step to assess the plot-scale variability of SOC stocks, a total of 16 soil cores were taken from each site at random, but slightly clustered positions within the 20 × 20 m plot. The random clustering was to ensure a balanced mix of small, intermediate and large distances (acronym for horizontal distance in the entire manuscript) between sampling points, enabling the evaluation of spatial dependence of the assessed parameters. Histograms were used to visually inspect the balance of paired distances between sampling points. The maximum distance between sampling points was set to 28.28 m, which is the diagonal distance of a 20 × 20 m square. In the field, a soil corer of 6.7 cm diameter was used to take an undisturbed sample of the soil at each random location to a depth of 50 cm, with soil depth increments of 0–10, 10–30 and 30–50 cm. If the core was compacted, the core length was measured and the length of each depth increment reduced proportionally (linear correction). However, the maximum core compaction that occurred was 5 cm (10%).

2.2 | Soil analysis and soil organic carbon stock calculations

For physical analysis (bulk density, rock fragment fraction, fine soil fraction, soil texture), soil samples from the profiles were oven-dried at 105°C, weighed and sieved to 2 mm. The sieved residuals were manually separated into stones and roots and weighed separately. The fine soil density of each individual depth increment *i* (FSD_i, g cm^{-3}) was calculated as:

$$FSD_i = \frac{mass_{fine\ soil}}{volume_{sample_i}}, \tag{1}$$

where $mass_{fine\ soil}$ is the mass of the particles <2 mm (g) and $volume_{sample}$ is the volume of the total sample (cm^3). We used *FSD* instead of total bulk density (*BD*) or bulk density of the fine soil ($BD_{fine\ soil}$), because it is the correct parameter for SOC stock calculation and can, in comparison to fine soil stock ($FSD \times depth$), be directly compared across depth increments of varying thickness (Poeplau et al., 2017).

For chemical analysis (total, organic and inorganic carbon, total nitrogen and pH), all samples were oven-dried at 40°C and sieved to 2 mm. An aliquot of each sample was milled for subsequent elemental analysis via dry combustion (LECO, St Joseph, MI, USA). Soil pH in water (H_2O) and calcium chloride ($CaCl_2$) with a soil:solution ratio of 1:5 as well as soil texture (clay <2, silt 2–63, sand >63 and <2000 μm) were measured for all three depth increments of the central profile (P1) from each site (Table 1). Soil samples with a $pH_{CaCl2} > 6.2$ were assumed to contain carbonates and were subjected to ramped dry combustion to distinguish organic carbon from inorganic carbon (LECO RC612).

All soil core samples were analysed using a LECO RC612, while all profile samples with pH <6.2 were analysed using a LECO TruMac. The soil core samples, for which physical and chemical properties were determined in the same sample, were dried at 40°C and an aliquot was dried at 105°C to determine the dry fine soil mass. The fine soil density of each individual depth increment of the core samples (FSD_i) was calculated in the same way as for the profile samples (Equation 1). SOC stocks (Mg ha^{-1}) for each individual depth increment (soil core or profile) were calculated as follows (Poeplau et al., 2017):

$$SOC\_stock_i = FSD_i \times SOC\_content_i \times depth_i \times 0.1, \tag{2}$$

where $SOC\_content_i$ is the content of SOC (g kg^{-1}) and $depth_i$ is the depth or thickness of the respective increment (cm). To evaluate treatment or temporal effects on SOC stocks, a comparison of equal soil masses ensures the most unbiased comparison (Ellert & Bettany, 1995; VandenBygaart & Angers, 2006). In theory, the sampling depth needs to be adjusted according to changes in bulk density. In practice, sampling is mostly done to an equal soil depth and mass-corrected SOC stocks are calculated to a given reference soil mass, as described in (Poeplau & Don, 2013). Here, the reference soil mass (RSM) was that of the central profile (P1).

2.3 | Statistics

To determine the random error made when soil profiles are shifted during resampling, three different strategies were compared as potential candidates for a resampling design for the German Agricultural Soil Inventory (Figure 1B):

Single: a single profile (P1, P2 or P3) representing the profile of the first inventory was shifted by 20–60 cm and resampled (one profile for initial sampling and one profile for resampling). The absolute deviation caused by each shift was averaged per site.

Single/Triple: the single initial profile (P1, P2 or P3) was resampled using three profiles (P1r, P2r and P3r) (one profile for initial sampling and three profiles for resampling). The deviation between P1, P2 or P3 and the mean of P1r, P2r and P3r was calculated and averaged for each site.

Triple: three profiles (P1, P2 and P3) were resampled with a further three profiles. This strategy would be applicable when a first resampling is conducted using three profiles and then resampled again by shifting each of the profiles (three profiles for initial sampling and three for resampling). The mean of the three profiles (P1, P2, P3) was compared with the mean of the three shifted profiles (P1r, P2r, P3r).

Subsequently, the mean absolute error (MAE) of all cropland and grassland sites was calculated for each of the three strategies (Goovaerts, 1998):

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |SOC_{initial_i} - SOC_{resampled_i}|, \tag{3}$$

where n is the number of sites, and $SOC_{initiali}$ and $SOC_{resampledi}$ are measured SOC contents or calculated SOC stocks for each site and scenario explained above. As a further indicator of the size of the error in SOC content caused by in situ spatial shifts during resampling, this error was compared with two laboratory errors of SOC determination: the within-sample heterogeneity (*subsampling error*) and the *analytical error* caused by the measurement itself. In order to quantify the *subsampling error*, a second aliquot was taken from each of the sieved P1 samples before milling, milled again and analysed using dry combustion. The *analytical error* was quantified by averaging the deviations between the two technical replicates of each original milled sample, which was done by default for each SOC measurement. The mean absolute percentage error (MAPE) was also calculated as an additional relative indicator of the sampling error:

$$MAPE = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{SOC_{initial_i} - SOC_{resampled_i}}{SOC_{initial_i}} \times 100 \right|. \tag{4}$$

The effect of the sampling design (*Single* vs. *Single/Triple* vs. *Triple*), sampling depth (0–10 cm vs. 10–30 cm vs. 30–50 cm) and land-use type and their interactions on MAE and MAPE were determined using three-way analyses of variance (ANOVA). This was done for the parameters SOC content, FSD and SOC stocks. In all three cases, data were log-transformed to ensure approximate normal distribution after visually checking model residuals. The Tukey-HSD test was performed as a post hoc test. Linear regression models were used to assess the effect of soil properties on the variability in SOC content. To select the best model, the dredge function was applied in the multi-model inference (*MuMIn*) package in R (Bartoń, 2009). Soil texture (sand, silt and clay content), root and rock fragment fractions, inorganic carbon content, soil pH and sampling depth were used as explanatory variables, and the relative sampling error (MAPE) in SOC content caused by the resampling of one profile with one profile (*Single*) was the dependent variable. Finally, profile data were also used to test the effect of the distance between two profiles on MAE of SOC stocks for significance using linear and logarithmic regression models.

The spatial dependence of FSD, SOC content and SOC stock differences at plot scale was assessed using the 16 soil cores taken from each site. The semi-variance γ was calculated first between all soil cores at each site as a function of the lag distance h (Schöning et al., 2006):

$$\gamma(h) = \frac{1}{2n(h)} \sum_{i=\%1}^{n(h)} [A_i(x_i) - A_i(x_i + h)]^2, \tag{5}$$

where n is the number of pairs separated by the lag distance h and A_i is the measured value of a given parameter at the location x_i. We did not fit semi-variogram models for each individual site, since the number of samples ($n = 16$) was far too low (Lark, 2000; Webster & Oliver, 1992). Instead, for an aggregated geostatistical evaluation across all sites, we first calculated average semi-variances in 2 m lag distance intervals at each site, and these average values were then assessed across all cropland and all grassland sites ($n = 8$ per interval and land use) using boxplots, which enabled a visual evaluation of potential trends (spatial dependencies) in the data.

All statistical analyses were performed in R version 3.5.2 (R Development Core Team, 2010). Significance was assessed at the $p < 0.05$ level.

3 | RESULTS

3.1 | Effect of sampling strategy on resampling error

The hypothetical resampling strategy had a significant effect on the estimated resampling error for FSD and SOC content and stock (Table 2). Across all depth increments, in both land-use types and for all considered soil parameters, the resampling of a single profile with one profile (*Single*) resulted in the highest average deviation (Figure 2) except in one case (SOC content at 30–50 cm depth in grassland soils). The *Single/Triple* strategy, in which a single profile of the initial sampling was resampled using three soil profiles, was found to cause intermediate resampling errors. The *Triple* strategy (three profiles resampled using a further three profiles) produced by far the smallest error. Increasing the number of profiles therefore led to a significant reduction in the resampling error. In 0–10 cm of cropland soils, the error in SOC content made by the *Triple* strategy was even smaller than the subsampling error in the laboratory expressing within-sample heterogeneity (Figure 2). Also, the overall MAPE of SOC content of the *Triple* strategy was not significantly different from the two considered laboratory errors (Figure 3). The average laboratory errors of SOC content caused by subsampling the same sieved sample and the analytical MAPE were 2.5 and 1.2% across all sites, depth increments and land uses (Figure 3).

The average resampling error in the mass-corrected SOC stock in 0–30 cm of croplands was 5.1 Mg ha^{-1} for *Single*, 3.5 Mg ha^{-1} for *Single/Triple* (error reduced by 31% compared with *Single*), and 2.5 Mg ha^{-1} for *Triple* (error reduced by 51% compared with *Single*). In grasslands, the absolute deviations in mass-corrected SOC stock in 0–30 cm were higher, with 7.6, 6.6 (–13%) and 3.8 (–50%) Mg C ha^{-1} for *Single*, *Single/Triple* and *Triple* (Table 3). Thus, even though the errors were greater in grasslands than in croplands, the error reduction from *Single* to *Triple* was the same (≈ 50%) as in the croplands. Both land-use types and all sampled depth increments were affected by the sampling strategy in a similar way, thus, no significant interactive effects of sampling strategy and land use or sampling strategy and depth were detected (Table 2). Mass correction tended to reduce the error in SOC stock caused by resampling for *Single*, while this was less pronounced for *Single/Triple* and *Triple* (Table 3).

TABLE 2 Results (p values) of the three-way analysis of variance (ANOVA) for mean absolute errors (MAE) and mean absolute percentage errors (MAPE) caused by resampling in soil organic carbon (SOC) content, fine soil density (FSD) and SOC stock ($n = 16$)

Independent variable	MAE			MAPE		
	SOC content	FSD	SOC stock	SOC content	FSD	SOC stock
Sampling strategy	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
Land use	<0.001	n.s.	n.s.	0.047	n.s.	n.s.
Depth	n.s.	0.005	0.002	<0.001	0.001	0.002
Sampling: land use	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.
Sampling: depth	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.
Land use: depth	<0.001	n.s.	n.s.	0.004	n.s.	n.s.
Sampling: land use: depth	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.

The independent variables were sampling strategy (*Single* vs. *Single/Triple* vs. *Triple*), land use (*cropland vs. grassland*) and soil depth (0–10 cm vs. 10–30 cm vs. 30–50 cm).

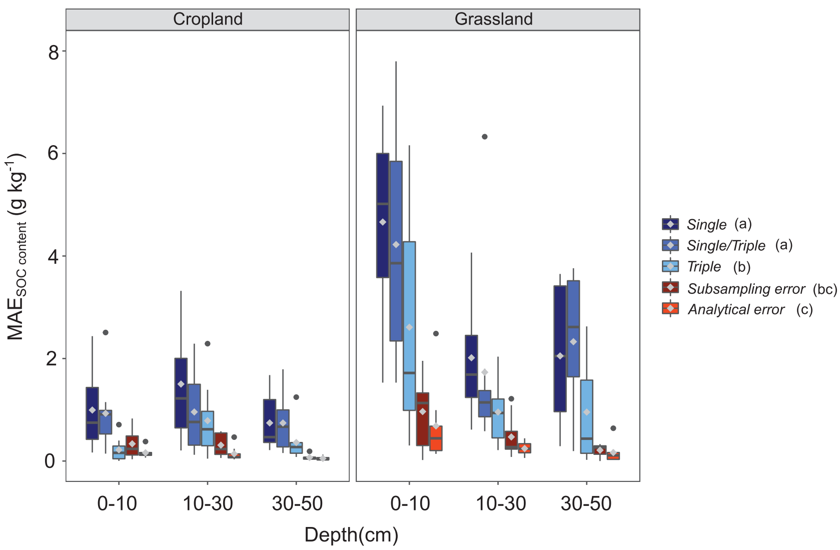

FIGURE 2 Mean absolute error (MAE) of soil organic carbon (SOC) content displayed as grey diamonds, with the distribution of the individual absolute errors of all sites ($n = 8$ per land use) displayed as boxplots for each depth increment and sampling strategy (*Single*, *Single/Triple*, *Triple*), as well as the errors caused by subsampling and the analytical error. Field heterogeneity-related errors are depicted in blue, laboratory errors in orange. Letters in brackets in the legend indicate significant differences between sampling strategies ($p < 0.05$)

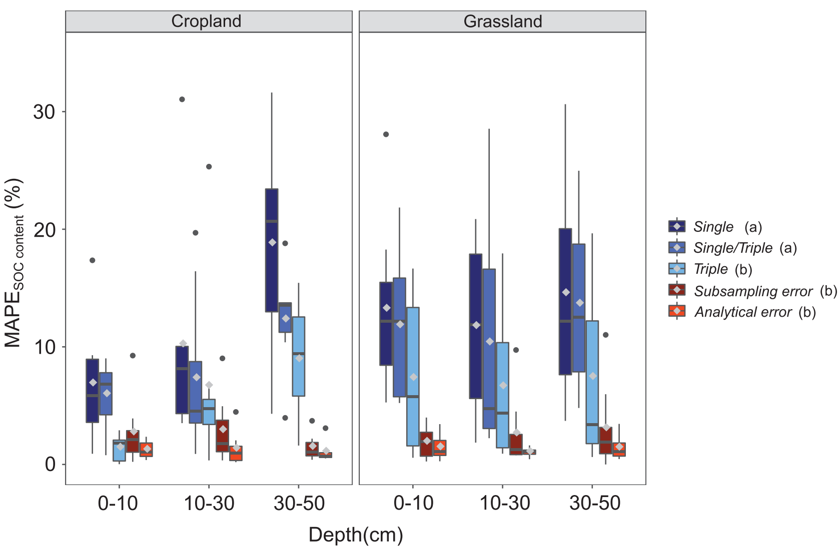

FIGURE 3 Mean absolute percentage error (MAPE) of soil organic carbon (SOC) content displayed as grey diamonds, with the distribution of the individual absolute errors of all sites ($n = 8$ per land use) displayed as boxplots for each depth increment and sampling strategy (*Single*, *Single/Triple*, *Triple*), as well as the errors caused by subsampling and the analytical error. Field heterogeneity-related errors are depicted in blue, laboratory errors in orange. Letters in brackets in the legend indicate significant differences between sampling strategies ($p < 0.05$)

TABLE 3 Mean absolute errors (MAE) for uncorrected and reference soil mass (RSM)-corrected cumulative soil organic carbon (SOC) stock (Mg ha^{-1}) ($n = 8$) for all three resampling strategies (*Single*, *Single/Triple*, *Triple*)

		Single		Single/triple		Triple	
Depth	Land use	Uncorrected	RSM	Uncorrected	RSM	Uncorrected	RSM
0–10	Cropland	2.2	2.1	1.6	1.8	0.9	1.3
0–30	Cropland	5.8	5.1	3.5	3.5	2.3	2.5
0–50	Cropland	6.6	6.4	2.2	2.2	2.7	2.3
0–10	Grassland	5.3	5.2	4.9	5.3	2.1	3.6
0–30	Grassland	8.1	7.6	6.6	6.6	4.9	3.8
0–50	Grassland	10.2	11.4	5.6	5.6	4.8	4.6

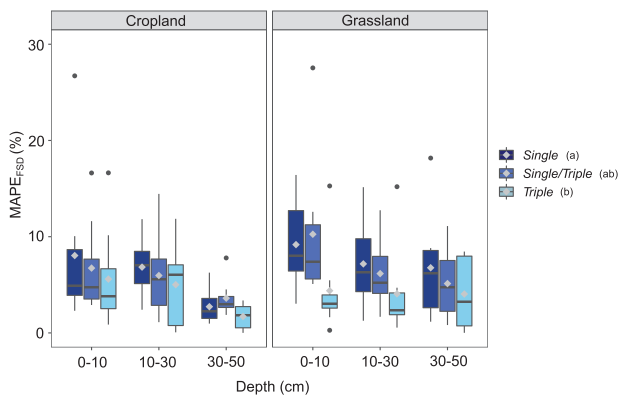

FIGURE 4 Mean absolute percentage error (MAPE) of the fine soil density (FSD, g cm^{-3}) displayed as grey diamonds, with the distribution of the individual absolute percentage errors of all sites ($n = 8$ per land use) displayed as boxplots for each depth increment and sampling strategy

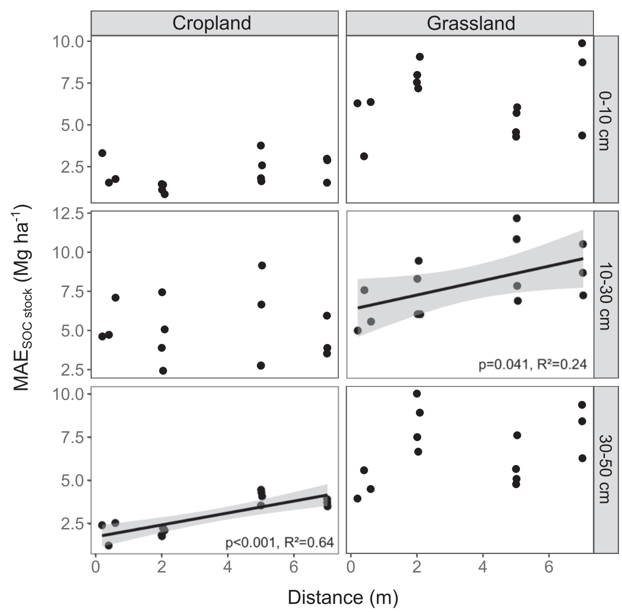

FIGURE 5 Mean absolute error (MAE) in soil organic carbon (SOC) stock as a function of the distance between two profiles. Each point represents the mean of eight sites. Regression models with a 95% confidence interval are only displayed when a significant effect of distance (linear or logarithmic) was detected ($p < 0.05$)

In grasslands, the MAE values were significantly higher than in croplands for all parameters (Figure 2). The relative error MAPE was significantly higher in grasslands, but this was not the case for the 30–50 cm depth increment where resampling of croplands tended to cause higher relative errors than resampling of grasslands (Figure 3). This explains the significant interactive effect of land-use type and depth on the MAPE of SOC content (Table 2). A higher MAPE in subsoils than in topsoil was expected, since SOC is less evenly distributed in subsoils, and much lower and cropland topsoils are also regularly homogenised. However, for grasslands, there was no clear depth dependence of the MAPE of SOC content. The MAPE of FSD was slightly lower than that of SOC (Figure 4) and showed a clear and significant decline with depth (Table 2).

Across sites, the distance between two soil profiles was rarely significantly correlated with the MAE of SOC stock (Figure 5). Only in the subsoil (30–50 cm) of cropland soils and the 10–30 cm depth increment of grassland soils was a significant increase in MAE detected with increasing distance within the first 7 m between soil profiles. Mostly, the deviations of SOC stock determined within a distance of less than 60 cm were comparable to those detected between profiles 5 or 7 m apart. In accordance with the geostatistical evaluation of the soil core samples, this indicates that in topsoils in particular, a large share of the maximum plot-scale variability in SOC stock can be expected to occur within the shortest distances <60 cm. There was no systematic effect of shifting soil profiles by 20, 40 or 60 cm on the MAE of SOC stock (Figure 5).

For 0–10 cm and 10–30 cm we were not able to explain a significant proportion of the variation in MAPE of SOC content across sites with the considered variables. However, in the 30–50 cm depth increment, the best model to explain the MAPE of SOC content included rock fragment fraction and silt content ($R^2 = 0.78$), while rock fragment fraction was positively correlated and silt was negatively correlated with the relative resampling error. The positive correlation with rock fragment fraction was the most important variable in 30–50 cm ($R^2 = 0.58$; Figure S1), in which the highest rock fragment fractions occurred. However, the direction was the same for all depth increments (data not shown). Across all sites and depth increments, the rock fragment fraction ranged from 0 to 17%.

TABLE 4 Average plot-scale coefficients of variation (%) and their standard deviation in fine soil density (FSD), soil organic carbon (SOC) content and stock for all sampled depth increments and both land use types separately

	FSD		SOC content		SOC stock	
Depth	Cropland	Grassland	Cropland	Grassland	Cropland	Grassland
0–10	8.3 ± 2.8	9.7 ± 2.7	7.7 ± 4.9	11.9 ± 5.5	9.3 ± 3.5	10.1 ± 3.7
10–30	6.5 ± 1.5	9.5 ± 6.9	8.8 ± 4.8	12.7 ± 4.5	10.2 ± 4.3	14.5 ± 8.0
30–50	6.5 ± 2.9	9.9 ± 7.0	27.6 ± 20.4	32.8 ± 20.9	25.8 ± 18.1	33.3 ± 18.8

Sixteen soil core samples were used to derive coefficients of variation for each site.

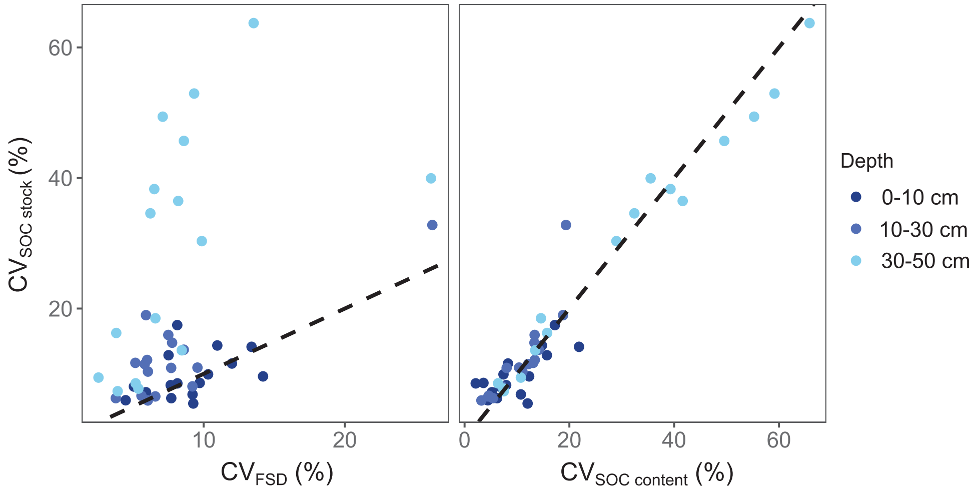

FIGURE 6 Coefficient of variations (CV) in soil organic carbon (SOC) stock of all sites as a function of CV in fine soil density (FSD) and SOC content at each site. CV were derived from 16 soil core samples at each site, and thus represent the plot scale (20 × 20 m). The dashed line indicates the 1:1 line

3.2 | General plot-scale variability and spatial dependence of assessed soil properties

The plot-scale variability of FSD, SOC content and SOC stock was slightly lower on average in croplands than in grasslands (Table 4). However, none of these differences was statistically significant, indicating that site had a greater influence than land use on the variability of the assessed parameters. The subsoil increment (30–50 cm) had CV about three times higher than the upper depth increments for SOC content and stock. In contrast, the variability of FSD tended to decrease with depth and was lowest in the subsoil. Across all depth increments, plot-scale variability in SOC content was a strong driver of the variability in SOC stock, while CV_{FSD} was only weakly correlated with $CV_{SOC\ stock}$ (Figure 6). In croplands, no clear trend of increasing semi-variance with increasing average lag distance across the 20 × 20 m plots was detectable (Figure 7). This was true for all depth increments and parameters. In grasslands, slight increases were visible in some cases, e.g., for SOC stocks in 0–10 and 10–30 cm in the lag distance range of >10 m (Figure 8). However, overall spatial dependence was weak. Semi-variances detected at smallest lag distances (<2 m) were in the same order of magnitude as semi-variances detected at largest lag distances (>18 m), which fits to the observations in the soil profile data, i.e., that small spatial shifts can cause large resampling errors.

4 | DISCUSSION

4.1 | Plot-scale variability in SOC

The average plot-scale variability in SOC contents and stocks observed in this study were comparable to those observed in microplots with a radius of 4 m by (Goidts et al., 2009). The average CV of about 8% in croplands and 12% in grassland topsoil SOC contents was however higher than the values reported by Saby et al. (2008), who found an average (median) CV of 3–4% for plots of 1–400 m^2 in European topsoils of various land-use types. This is only slightly higher than the reported analytical uncertainty of 2–3% given in the same study. In accordance with Goidts et al. (2009), we found the analytical error to be a negligible source of uncertainty (≈ 1%), when state-of-the-art methods are applied and the instrument is not changed. In the present study, the observed cropland and grassland topsoil SOC stock variability was much lower than the forest topsoil CV (>30%) observed by Schöning et al. (2006) on a similar spatial scale. For both land use types, subsoil

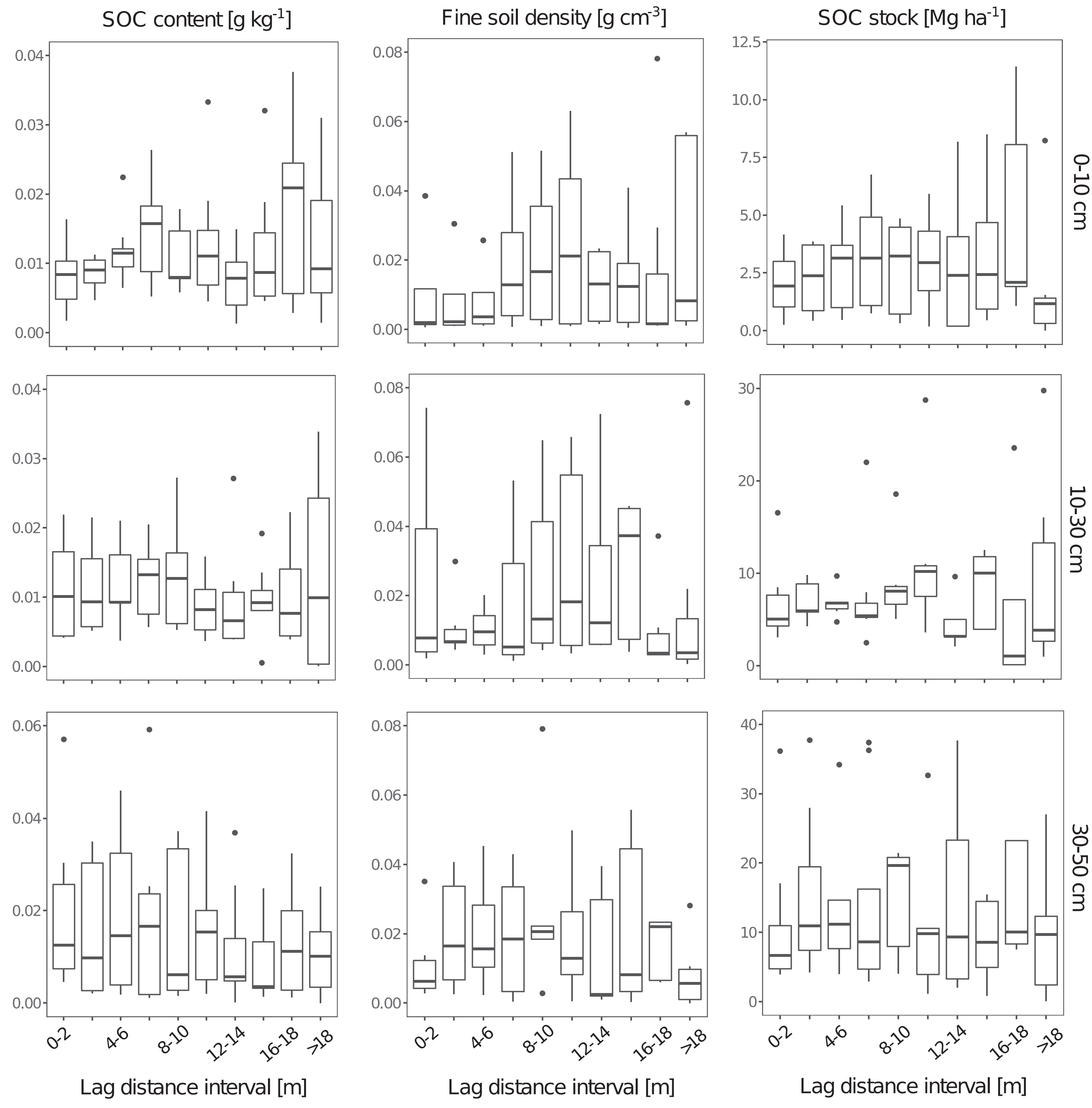

FIGURE 7 Boxplots of average semi-variances of soil organic carbon (SOC) content, fine soil density (FSD) and SOC stock at 2 m lag distance intervals for all croplands sites ($n = 8$). On average, 12 semi-variances were averaged per site and interval

(30–50 cm) SOC variability was almost three times as high as topsoil variability. The higher CV of SOC in agricultural subsoils than in topsoils has been observed before (Don et al., 2007) and can be explained by the patchiness of organic C inputs in subsoils, inhomogeneities of the geogenic substrate (Heinze et al., 2018) and the absence of anthropogenic homogenisation (croplands). For FSD, the opposite trend to SOC was observed, i.e., a decrease in variability with increasing depth, which was most likely related to the low degree of disturbance in the subsoil and the constant overburden pressure of the overlaying solum (Gao et al., 2016). FSD was generally less variable than SOC, which was also observed by Goidts et al. (2009) and Don et al. (2007). Accordingly, in contrast to FSD, the variability in SOC content was a good predictor of the variability in SOC stock.

The content and stock of SOC is driven by abiotic site factors such as climate and mineralogy (Doetterl et al., 2015), but also by carbon inputs (Kätterer et al., 2012). While climatic drivers are mostly relevant on larger scales, such as continents or regions with strong gradients (Hobley et al., 2015; Wiesmeier et al., 2013), geological, pedological, geomorphological or hydrological drivers can be of major importance at field to landscape scale (Doetterl et al., 2016; Hook & Burke, 2000).

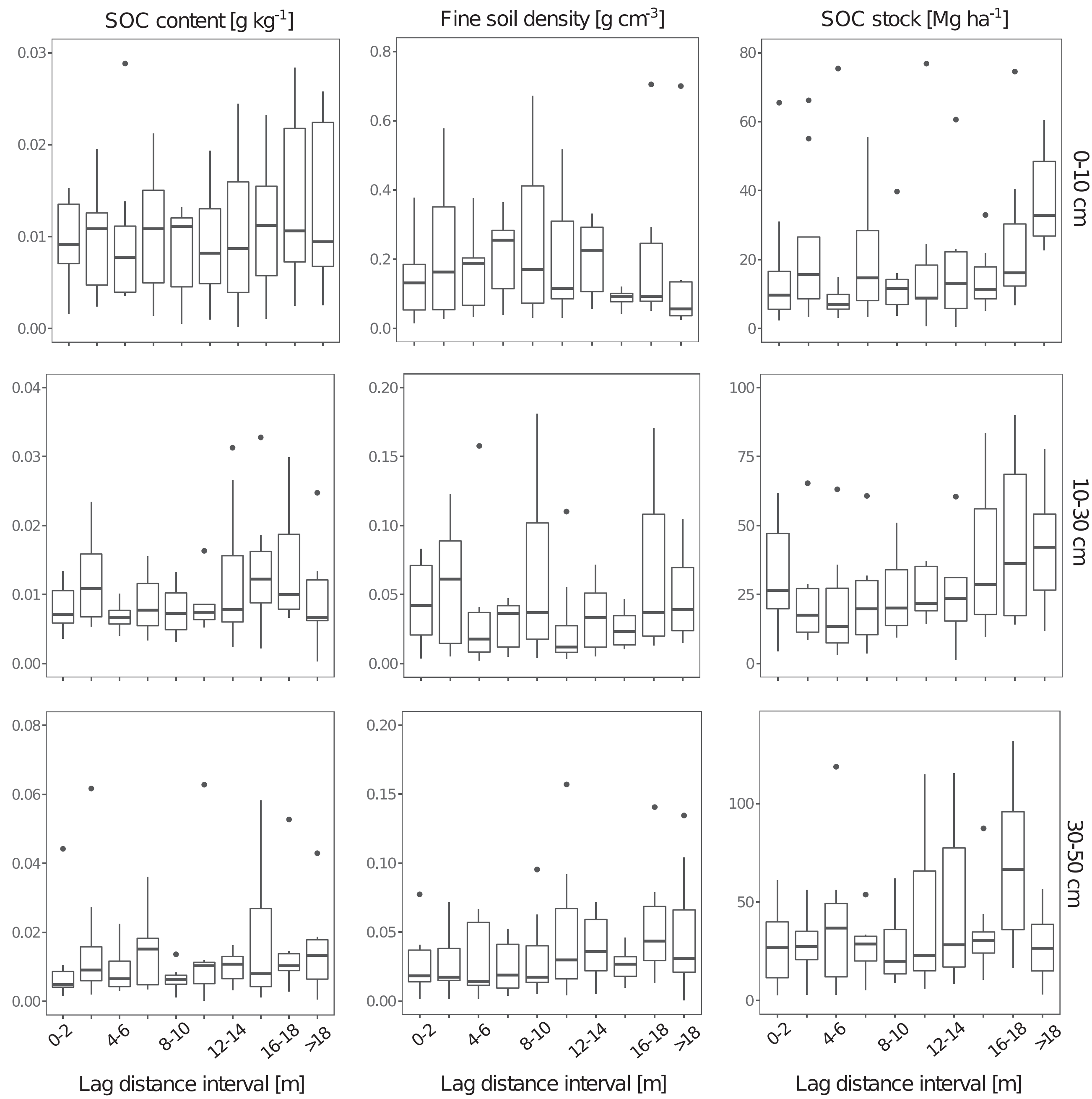

FIGURE 8 Boxplots of average semi-variances of soil organic carbon (SOC) content, fine soil density (FSD) and SOC stock at 2 m lag distance intervals for all grassland sites ($n = 8$). On average, 12 semi-variances were averaged per site and interval

On a plot scale these abiotic drivers might be less important for SOC variability or are partly cancelled out by plot selection using visual criteria. However, even within small and apparently homogeneous plots, the small-scale variability in SOC and other soil properties can be large, as shown in the present study. Sporadically, soil profiles with outlying pedogenic properties in the subsoil were encountered within a distance of 7 m. A typical example is silt lenses in sandy, glacio-fluvial deposits (Sumbler, 1983). Substrate inhomogeneities, even within the same substrate or geological unit, are thus also likely to explain parts of the SOC variability at plot scale. Apart from the homogenised plough layer of croplands, the spatial heterogeneity of carbon inputs, as well as the more or less random redistribution of organic matter by bioturbation might also play a significant role in SOC stock variability at plot scale. The proximity of a sampling point to larger plants, the distribution of aboveground and belowground biomass in general, macropore networks of roots or earthworms that are preferentially reused by plants or filled with C-rich material, patches of urine in pastures causing species shifts and thus carbon input differences, patches of dung or even unequally distributed mineral fertilisers can all cause variability in SOC. In all of these examples such variability can occur abruptly and within shortest distances. Such initial patchiness may result in positive feedbacks, with higher C input to these patches over longer time periods resulting in changes in total SOC stock at this scale. Wiesmeier et al. (2009) detected strong differences in small-scale SOC variability between overgrazed and less degraded steppe soils in 2×2 m plots and suggested using such variability as an indicator of degradation. Finally, the combination of small-scale substrate inhomogeneities and patchiness of SOC inputs plus the strong homogenisation in cropland topsoils are likely to cause the weak spatial dependence in SOC stock and related parameters.

4.2 | Sampling strategy effect on the random error in SOC stock and related parameters

The results of this study suggested that much of the variability in SOC stock at plot scale is observed within shortest distances. Consequently, the resampling error associated with a shift of a single soil profile by <1 m was not at all negligible. Instead, it was as great as if the profile had been shifted by as much as 7 m. Shifting a single profile by 40 cm on average caused average SOC stock deviations of 5.1 and 7.6 Mg C ha^{-1} at 0–30 cm depth in cropland and grassland soils. This might not affect average national or regional-scale SOC stocks estimated by soil inventories, since the error was random and the systematic error (bias) might be close to zero given a sufficiently large number of sites. However, the error exceeded the maximum range of management-related SOC stock changes that can be expected between two sampling events at a suggested interval of 10 years (Schrumpf et al., 2011). For example, in a synthesis of review papers on agricultural measures to increase SOC stocks, Bolinder et al. (2020) found average 10-year increases in SOC of 4.1 Mg C ha^{-1} for manure application, 3.3 Mg C ha^{-1} for cover crops (when grown every year) and 1.2 Mg C ha^{-1} for straw retention. Realistic management-related SOC stock changes are thus highly unlikely to be detected at plot scale by resampling just one soil profile. Thus, resampling a single soil profile, even with a minimum shift of just 20–60 cm, would probably fail to elucidate agricultural management effects on SOC stock changes at any given site. Across sites, the absolute error between the initial and resampled profile ranged from 1.8 to 13.7 Mg C ha^{-1}. In a national inventory context, the correlation between SOC stock at sampling date one and sampling date two would thus be characterised by a huge scatter around the 1:1 line, with residues primarily explained by the random sampling error. This was similarly observed by Heikkinen et al. (2013) for the Finnish agricultural soil inventory and in the LUCAS soil survey (Fernández-Ugalde et al., 2020).

Interestingly, in the present study the mean absolute error in SOC content increased significantly with rock fragment fraction, while it decreased with silt content. The latter can be explained by the fact that silty soils, such as the Chernosems developed from loess at the C1 site, are often homogeneously structured, facilitating a homogeneous distribution of SOC due to homogeneous plant growth and potentially also by bioturbation. The positive correlation of rock fragment fraction and the resampling error could indicate that the distribution of SOC along the soil profile is patchier in more rocky soils, e.g., due to more preferential root growth. At the same time, with a maximum of 15% the rock fragment fraction was most likely not high enough for such a mechanism in this study and might thus simply indicate substrate inhomogeneity as such.

When the resampling of one profile was performed using three individual profiles, the resampling error decreased compared with resampling with just one profile. Despite the fact that values of one profile were compared to the average values from three profiles from up to 7 m away, the error in SOC content, FSD and SOC stock could be reduced compared with a simple shift of one profile by 20–60 cm. This is in line with the findings of Goidts et al. (2009), who suggest that the small-scale variability in SOC content can be decreased by composite sampling, i.e., increasing the number of individual samples. Accordingly, the lowest resampling error was observed with the *Triple* strategy, i.e., resampling three profiles with a further three profiles. For the 0–10 cm depth increment of the investigated croplands, this resampling error was even smaller than the deviation between two subsamples of the same dried and sieved sample (*subsampling error*). In other words, at least for this specific depth increment, the small-scale variability was almost entirely accounted for and the associated resampling error cannot be expected to be reduced much further, e.g., with more than three additional soil profiles. As expected, the analytical error with repeated measurements of the same subsample was much lower than the other sources of uncertainty and can be considered negligible, at least for values above the detection limit (Saby et al., 2008). As expected, increasing the number of profiles from one to three also reduced the minimum detectable difference of SOC stocks by up to 70% for the *Triple* strategy.

4.3 | Implications for soil sampling

The aim of this study was to develop a resampling design for the German Agricultural Soil Inventory. One of the specific features of this inventory was that a profile pit was dug and described in detail to a depth of 1 m. Soils were not only characterised by their soil physical and chemical properties, but a wealth of pedological data was also evaluated from the soil profile (Poeplau et al., 2020). In addition to the soil profile, eight soil cores in a circle of 20 m diameter around the profile pit were taken. Those soil cores were analysed individually for a part of the inventory sites, revealing a significant bias between profile and soil core-estimated SOC stocks (Jacobs et al., 2018). This can be partly explained by soil compaction during core sampling and the applied linear correction of that compaction, which was also observed by (Walter et al., 2016) and in the present study (data not shown). However, a bias in SOC content was also found, which is more difficult to explain. In any case, this bias and the fact that the baseline was derived from profile sampling hindered the use of soil cores for resampling, since systematic errors caused by a switch in methods would increase the total error. Several other inventories have based their sampling strategies on composite soil core samples covering one or several plots at a site (Heikkinen et al., 2013; Orgiazzi et al., 2018; Poeplau et al., 2015). The major advantage of a composite core sample is its robustness and the chance of minimising the spatial variability effect on the resampling error (Goidts et al., 2009). If the goal is to take a representative sample of a whole plot or field and to verify changes on that scale, then core or auger sampling is preferable due to the large sample sizes needed to cover a larger area. However, in national inventories this is not the case, since the sample should be representative for one whole grid cell (8 × 8 km in the case of the German Agricultural Soil Inventory). A pooled sample from a profile pit might then be just as representative. Regarding resampling, one major problem with soil cores is that variations in soil moisture conditions in particular will lead to variable soil compaction and thus a sampling bias. This might partly explain the wide deviations between two sampling dates, as observed by Heikkinen et al. (2013). Soil profiles are certainly more robust in that respect. The present study was not designed to directly compare the two approaches, but both have shown that shifting a sampling location even by small distances of <1 m induces a significant error in SOC stock estimates. Therefore, in the case of the German Agricultural Soil Inventory, more than one profile needs to be sampled to retain the possibility of verifying potential management effects on SOC stocks in a repeated inventory. The present study was not directly designed to investigate, if three profiles are sufficient for a robust first resampling. However, we sampled a total of six profiles per site, so a potential resampling with of the initial profile with four or five profiles could be checked (Table S1). In fact, resampling one profile with four or five profiles can lead to a slight further reduction of the resampling error (≈ 2%), but the response was flattening and the optimal number depends on cost-benefit considerations.

The average error was generally smaller at microplot scale than at plot scale. This implies that paired sampling, i.e., the establishment of sub-plots within a larger plot, experiment or field, is a valid means to also decrease the minimal detectable difference to some extent, which has been highlighted also by Schöning et al. (2006). However, many studies reported that up to several hundred samples are required to detect small changes (≈1–3 Mg ha^{-1}) at the field scale (Heikkinen et al., 2021; Schöning et al., 2006; VandenBygaart, 2006). This should be of interest for emerging carbon certification schemes in particular, and questions whether field-scale verification of SOC stock changes is feasible after a few years at all, at least when moderate or large-scale realisable measures of C sequestration are being targeted. However, new technologies for cost-efficient and spatially accurate SOC determination are being developed (de Gruijter et al., 2018) and proximal sensing has lately been found to be more accurate yet only slightly more expensive than composite sampling in estimating average SOC stocks at field scale (Viscarra Rossel & Brus, 2018). The authors concluded that the cost efficiency, i.e., the ratio of accuracy and costs, was 1.2–2.1 higher for handheld sensing (visible-near infrared and gamma attenuation) as compared to composite sampling. To date, it can be doubted that the accuracy of the techniques is high enough for detecting management-induced SOC changes in any given situation (Jaconi et al., 2017). However, major advantages of spectroscopic methods over composite sampling are that (1) information on the spatial distribution of SOC can be obtained, which can also facilitate the design of sampling schemes (Viscarra Rossel & Brus, 2018) and (2) that a wide range of soil properties can be estimated from the spectra (Cécillon et al., 2009).

5 | CONCLUSIONS

This study is among the first to combine the quantification of plot-scale and microplot-scale heterogeneity of SOC stock and associated parameters in agricultural soils. It revealed a relatively high variability in SOC stock-related parameters within distances of <1 m. Consequently, even a precise relocation and resampling of these profiles, i.e., shifting the sampling locations just a few decimetres, would lead to resampling errors that exceed the potential effect of realistic agricultural management effects on SOC stocks at a monitoring interval of 10 years. Increasing the number of soil profiles to three was shown to greatly decrease the random sampling error in both croplands and grasslands, since it accounted for small-scale variability. Furthermore, the minimum detectable difference was decreased when three profiles rather than one were used for resampling. The probability of verifying changes in SOC stocks on a country scale or within specific strata can thus be significantly improved by this extra effort. Overall, this study confirmed earlier findings that the in situ spatial heterogeneity of SOC content is the major uncertainty when estimating SOC stocks and that to some extent this issue can be addressed by composite or replicate sampling. The large sample sizes needed to verify SOC stock changes over time in a single field or plot, however, calls into question the practicability of such efforts and likewise of emerging carbon certification initiatives aimed at plot and field-scale detection of SOC stock changes within short time periods.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available in Zenodo at https://doi.org/10.5281/zenodo.5841415.

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SUPPORTING INFORMATION

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