https://doi.org/10.5194/soil-2021-81
Preprint. Discussion started: 27 August 2021

Soil organic matter and labile fractions depend on specific local parameter combinations

Malte Ortner[1], Michael Seidel[2], Sebastian Semella[2], Thomas Udelhoven[3], Michael Vohland[2], Sören Thiele-Bruhn[1]

[1]Soil Science Department, University of Trier, Trier, 54296, Germany
[2]Geoinformatics and Remote Sensing, Institute for Geography, Leipzig University, Leipzig, 04103, Germany
[3]Department of Remote Sensing & Geoinformatics, University of Trier, Trier, 54296, Germany

Correspondence: Malte Ortner (ortner@uni-trier.de), Sören Thiele-Bruhn (thiele@uni-trier.de)

Abstract. Soil organic matter (SOM) is an indispensable component of terrestrial ecosystems. Soil organic carbon (SOC) dynamics are influenced by a number of well-known abiotic factors such as clay content, soil pH or pedogenic oxides. These parameters interact with each other and vary in their influence on SOC depending on local conditions. To investigate the latter, the dependence of SOC accumulation on parameters and parameter combinations was statistically assessed that vary on a local scale depending on parent material, soil texture class and land use. To this end, topsoils were sampled from arable and grassland sites in southwestern Germany at four regions with different soil parent material. Principal component analysis (PCA) revealed a distinct clustering of data according to parent material and soil texture that varied largely between the local sampling regions, while land use explained PCA results only to a small extent. The obtained global and the different local clusters of the dataset were further analyzed for the relationships between SOC and mineral phase parameters in order to assess specific parameter combinations explaining SOC and its labile fractions. Analyses were focused on soil parameters that are known as possible predictors for the occurrence and stabilization of SOC (e.g. fine silt plus clay and pedogenic oxides). Regarding the global dataset, we found significant correlations between SOC and its labile fractions hot water-extractable C (HWEC) and microbial biomass C (MBC), respectively and the predictors, yet correlation coefficients were partially low. Mixed effect models were used to identify specific parameter combinations that significantly explain SOC and its labile fractions of the different clusters. Comparing measured and mixed effect models-predicted SOC values revealed acceptable to very good regression coefficients (R^2 = 0.41-0.91). Thereby, the predictors and predictor combinations clearly differed between models obtained for the whole data set and the different cluster groups. At a local scale site specific combinations of parameters explained the variability of organic matter notably better, while the application of global models to local clusters resulted in less sufficient performance. Independent from that, the overall explained variance generally decreased in the order SOC > HWEC > MBC, showing that labile fractions depend less on soil properties than on organic matter input and turnover in soil.

https://doi.org/10.5194/soil-2021-81
Preprint. Discussion started: 27 August 2021

1 Introduction

Soil as an inherent part of terrestrial ecosystems acts as a major regulator of the organic carbon (OC) cycle especially through the function of OC storage (Heimann and Reichstein, 2008; Scharlemann et al., 2014). Hence, it is of utmost relevance and a focus of ongoing research to define models and parameter sets that best describe and predict soil organic carbon (SOC) contents of soils. Further it is required to identify the driver for SOC storage at different scales and sites to adapt the management of soils. Overall, the relevance of parameters for quantification of SOC is often described by bivariate relationships (Hassink et al., 1993; Barré et al., 2017). Yet, SOC and its potential sequestration by formation of organo-mineral associations depends on combinations and interactions of several environmental factors or soil properties, so that the number of multivariate applications to estimate the accumulation of SOC is increasing (Hobley et al., 2015; Heinze et al., 2018).

In addition to total SOC, its labile subfractions such as hot water extractable carbon (HWEC) or microbial biomass carbon (MBC) are more and more recognized as fast reacting SOC pools in order to analyze carbon dynamics in soils (Weigel et al., 2011; Lal, 2016). The HWEC is known as a measure of the bioavailable and mineralizable fraction of SOC (Spohn and Giani, 2011; Heller and Zeitz, 2012). The MBC is a quantitative measure of the microbial community that plays an indispensable role for the turnover of SOC. Therefore, MBC is expedient to explain SOC dynamics (Liang et al., 2017). In contrast, much less research and attempts for quantitative modeling of these labile fractions compared to SOC have been done in the past (Liddle et al., 2020).

It is well known that factors such as climate, topography, vegetation, parent material and time are major factors influencing contents and storage of SOC (Jenny, 1941). Accordingly, large scale (often national or continental) surveys often include geographical properties, vegetation types, general forms of land use as well as climatic site conditions to explain the variability of SOC (Wiesmeier et al., 2014; Gray et al., 2015). Consequently, vegetation and anthropogenic influence by land use and land use changes are essential factors to model SOC accumulation and dynamics (Poeplau and Don, 2013; Dignac et al., 2017). The relevance of the parent material for SOC sequestration and stocks was discussed for sites and small landscapes of a few km² (Barré et al., 2017; Angst et al., 2018) as well as for large areas on the scale of regions or countries (Wiesmeier et al., 2013; Vos et al., 2019). The potential influence of parent material on SOC is mostly considered by parameters of soil mineralogy and texture (Herold et al., 2014). Factors such as climate, topography, parent material, vegetation or land use are well suited to explain the variability of SOC at larger scales or at landscapes with a high variability concerning these factors. In contrast, for smaller, local study areas or rather uniform areas with a low factor variability an inclusion of these factors as variables is less expedient (Wiesmeier et al., 2019).

In addition to or even instead of these general factors, further parameters describing the soil composition in a more specific way, become relevant at regional or local scale setting boundaries for SOC accumulation, e.g. by the formation of organo-mineral associations. For an identification of SOC variations due to site specific characteristics selected parameters are used which are mostly known as indicators for stabilization of SOC such as content of fine silt, clay and pedogenic oxides or microbial parameters such as microbial biomass and amino sugars (Angst et al., 2018; Quesada et al., 2020). There are indications that for the explanation of SOC variability on a local to regional scale soil parameters instead of factors are especially suitable. Models based on soil parameters also allow to identify possible drivers of SOC stabilization while using the above mentioned general factors would not deliver a satisfying result (Wiesmeier et al., 2019; Adhikari et al., 2020).

Organo-mineral associations are highly relevant for stabilization and accumulation of SOC and its labile fractions (Lützow et al., 2006). It is well known that the different mineral particle size classes vary in their ability to interact with SOC, forming organo-mineral associations (Arrouays et al., 2006; Lützow et al., 2007). On one hand coarse particle size fractions such as sand, coarse silt (cSilt) and medium silt (mSilt) contribute less to interactions between SOC and the mineral phase while on the other hand fine silt (fSilt) and clay dominate such interactions (Ludwig et al., 2003). In addition, the mineral composition of the fine fraction, i.e. types of clay minerals and pedogenic oxides, is relevant for the interactions of SOC with the mineral phase (Kleber et al., 2015; Porras et al., 2017). Especially iron and aluminum oxides interact with SOC leading to sequestration (Mikutta et al., 2006). Stabilization of SOC is further enhanced by multivalent cations such as Ca^{2+} and Mg^{2+} going along with higher soil pH (Kaiser et al., 2012; O'Brien et al., 2015). Covering on one hand all quantitative relevant cations and on the other hand being an overall measure of soils sorptive

https://doi.org/10.5194/soil-2021-81
Preprint. Discussion started: 27 August 2021

properties the effective cation exchange capacity (ECEC) provides an overall measure to model cation impact on SOC storage (Kaiser et al., 2012; O'Brien et al., 2015). Rock fragments (soil skeleton) contribute only little to SOC storage (Poeplau et al., 2017). Anyhow, the fraction of rock fragments is considered as a relevant parameter to assess SOC accumulation due to a potential saturation effect in soils with a high rock fragment content in consequence of a disproportionately high input of organic matter in the fine soil fraction (Bornemann et al., 2011).

Consequently, understanding SOC as a dynamic equilibrium of heterogeneous compounds with distinct relationships to various components of the soil mineral phase (Lehmann and Kleber, 2015) implements that SOC accumulation is best described and predicted by a variety of soil mineral phase parameters instead of a single predictor. Thereby combinations of parameters or factors can differ according to the considered scale. Consequently, multivariate approaches better explain the SOC variability (Heinze et al., 2018; Liddle et al., 2020) compared to bivariate correlation models that are often unsuited at the level of local and regional soilscapes (Jian-Bing et al., 2006). The latter especially applies for studies that are limited to a single specific location or only contain a limited number of categorical variables or estimated soil parameters (Liddle et al., 2020). On the other hand, predictions based on global models are often less site-specific and thus can possibly lead to an insufficient quantification of SOC at certain sites. Consequently, it is required to determine parameter sets to estimate SOC and its labile fractions HWEC and MBC at a regional or landscape scale. It is necessary to identify predictor parameters and categorical environmental factors that are able to predict SOC as well as its labile fractions by using local and global models. Differences regarding the relevance of a predictor in local vs. global models have to be identified to boost model performance and to fit adequate datasets using the best set of parameters for the prediction of SOC at the investigated location. This overall aim was investigated in this study using a dataset from four local agricultural areas in the greater region of Trier (each with a size of 5-10 km²), thus with similarity in the global factors but distinct local properties such as parent rock material, soil texture and land use. Regarding the composition of the soil mineral phase the four local areas differ among each other, but as a global dataset they represent a broad range of soil properties typical for soils in temperate regions. Therefore, the dataset enables to verify whether the global dataset is able to cover the local variability of SOC and its labile fractions. Objectives of this study were, (i) based on identified differences in soil properties to determine best fitting factors and parameter combinations that explain the variability in SOC and its labile fractions HWEC and MBC. (ii) It was aimed to determine the relevance of local models in comparison to global models to achieve a sufficient quantification for local landscapes with distinct properties. To this end, linear regression, principal component analysis (PCA) and mixed effect models were used in order to find out whether global models or local models are better fitting. (iii) It was assessed if local datasets show a distinct combination of significantly contributing predictor parameters compared to other local datasets and the entire dataset.

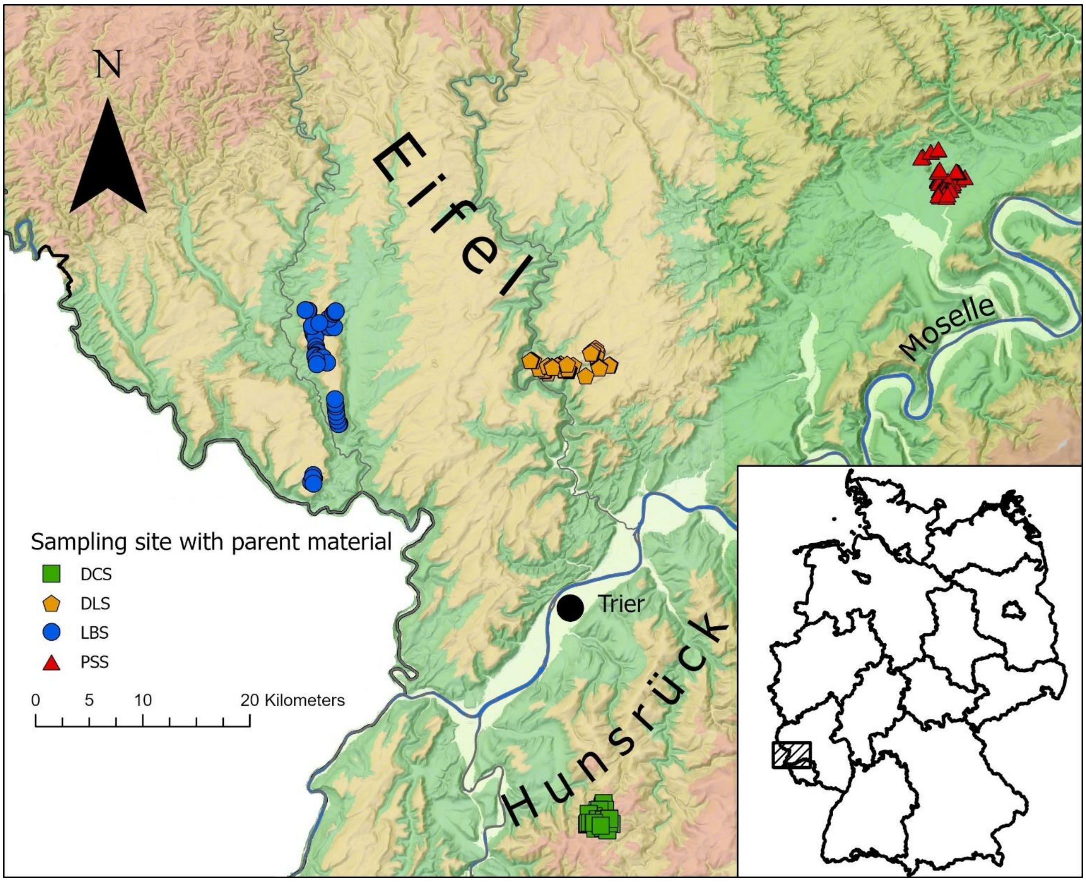
2 Material and Methods

2.1 Study area

The study was conducted in the greater area of Trier in southwestern Germany (Fig. 1). Bulk samples from topsoil horizons, i.e. 0-25 cm for arable and 0-15 cm for grassland soils, were taken in spring 2017 and 2018 from 199 agricultural sites used as arable land (150) and grassland (49). Similar numbers of samples were taken from four regional areas with different parent materials. Parent materials were Devonian clay schist (DCS), Luxemburg sandstone (LBS), sandy dolomitic limestone (DLS) from the Muschelkalk, and Permian siltstone and fine sandstone (PSS) from the Rotliegend (Wagner et al., 2011).

https://doi.org/10.5194/soil-2021-81
Preprint. Discussion started: 27 August 2021

Fig. 1. Study area in the greater Trier region; sampling sites at the four regions with different parent material are indicated, i.e. Devonian clay schist (DCS), sandy dolomitic limestone (DLS) from the Muschelkalk, Luxemburg sandstone (LBS), and Permian siltstone and fine sandstone (PSS) from the Rotliegend (©GeoBasis-DE).



2.2 Analysis of soil properties

Samples were sieved < 2 mm and the stone content (> 2 mm) was determined gravimetrically. For further analysis, samples were divided and stored at -20°C or air-dried, respectively. Soil pH was measured in 0.01 M $CaCl_2$ solution using a pH/Con 340i glass electrode (WTW GmbH, Weilheim). Particle size distribution was determined by a combination of wet sieving and pipette method according to Blume et al. (2011). Dithionite-citrate extractable Fe (Fe_d) was measured according to Mehra and Jackson (1958). To this end, 2 g air-dry soil were extracted with a mixture of 1 g sodium dithionite, 40 ml sodium citrate and 10 ml $NaHCO_3$. Oxalate extractable Fe and Al (Fe_o, Al_o) were determined according to Schwertmann (1964). For extraction, 1 g air-dry soil was shaken for 2 h in the dark in 50 ml NH_4^+-oxalate (pH 3) and filtered afterwards. Extraction for the determination of the effective cation exchange capacity (ECEC) was conducted using 1 M NH_4Cl. Elemental analyses for pedogenic oxides and ECEC (Na, K, Fe, Mn, Al, Ca, Mg) were done using atomic absorption spectrometry (Varian AA240 FS Fast Sequential Atomic Absorption Spectrometer; Darmstadt, Germany).

For estimation of total carbon (TC) and nitrogen soil was dried at 105°C, grinded and measured by an Elemental Analyzer EA3000 Series (HEKAtech GmbH, Wegberg). For carbonate containing soils the inorganic carbon (IC) was determined following carbonate

https://doi.org/10.5194/soil-2021-81
Preprint. Discussion started: 27 August 2021

destruction using phosphoric acid at a temperature of 100°C (IC Kit combined with Elemental Analyzer EA3000 Series, HEKAtech GmbH, Wegberg). SOC content was calculated as the difference of TC and IC. HWEC and hot water extractable nitrogen (HWEN) were determined following Körschens et al. (1990), using a Gerhardt Turbotherm TT 125 (Gerhardt, Bonn, Germany) for extraction of 10 g soil with distilled water (50 ml) at 100°C for 1 h. After extracts cooled down 1 ml of 0.2 M $MgSO_4$ was added and samples were centrifuged at 1476 g for 10 minutes. Microbial biomass was estimated by using chloroform fumigation extraction according to Joergensen (1995) with 0.01 M $CaCl_2$. Extracts of HWEC, HWEN, microbial biomass carbon (MBC) and nitrogen (MBN) were analyzed with a TOC-VCPN analyzer (Shimadzu, Duisburg, Germany). For MBC and MBN correction factors kEC = 0.45 and kEN = 0.4 respectively, were used (Joergensen, 1996; Joergensen and Mueller, 1996). Soil respiration was measured according to Heinemeyer et al. (1989) . Therefore, 25 g dry equivalent of sieved field moist soil were weighted in a tube that was flushed with 200 mL min^{-1} of CO_2-free, humid air for 24 hours. Evolved CO_2 was determined after the soil passage using an infrared gas analyzer (ADC 225 MK3, The Analytical Development, Hoddesdon, England).

2.3 Data analysis

Principal component analysis (PCA) was carried out to identify clusters within the dataset. For that purpose, 24 parameters describing the mineral phase as well as SOM were included (Table 1). To conduct the PCA applied variables were log transformed, centered and scaled to achieve standardized and comparable variables. Ellipses were defined by 95 % of the confidence interval according to Fox and Weisberg (2019), The cluster of clayey soils was not included in the analysis due to a small number of samples (n = 5). Linear regressions were performed to identify significant impact of mineral phase parameters on SOC, HWEC and MBC for the entire dataset as well as for the identified clusters. Mixed effect models were determined for the entire dataset and for identified clusters. To this end, selected soil properties of the mineral phase (Fe_{d-o} [g/kg], Fe_o [g/kg], Al_o [g/kg], sand [%], cSilt plus mSilt [%], fSilt plus clay [%], $(Ca + Mg)_{ECEC}$ [mmolc/kg], stones [%] and pH) were used as fixed effect while, 'parent material', 'soil texture group' or 'land use' were used as random effect. In general, as random effects only categorical variables were selected, while for the fixed effects variable mineral phase parameters were selected. Parent material as a random effect includes the four different soil parent materials that dominate at the four sampling sites. For the soil texture group as random effect four levels were applied (sandy, silty, clayey and loamy soils). The additional implementation of the soil texture groups was done to consider the potential different intercepts of the specific groups. Land use as random effect comprised the two management practices arable and grassland. Maximum likelihood was applied as estimation procedure for the mixed effect models. At the beginning, all selected soil properties were included in each model. Stepwise removal of parameters was conducted until all properties included in the models significantly contributed to SOC, HWEC or MBC, respectively. Additional, the relevance of variables was visualized by the mean values of the clusters multiplied with their coefficient received from the mixed effect models. To avoid collinear behavior of the soil texture related parameters either 'sand' or 'coarse silt plus medium silt' (cSilt plus mSilt) were used for model development. The two models received were compared by their Akaike information criterion (AIC) using ANOVA to identify the best model. Furthermore, ECEC was excluded from mixed effect models to avoid overfitting due to collinearity with $(Ca+Mg)_{ECEC}$. Residuals of models were examined for homoscedasticity and normality. In case these criteria were not fulfilled, the response variable was square root transformed to achieve variance homogeneity and normality. To examine performance of mixed effect models, predicted values were tested against measured values of SOC, HWEC and MBC, respectively using linear regressions. Data are shown as mean (± SE) if not indicated otherwise. Statistical significance was indicated with *$p < 0.05$, **$p < 0.01$ and ***$p < 0.001$. Statistical analyses were carried out using the R statistical package version 3.6.2 (R Core Team, 2019).

https://doi.org/10.5194/soil-2021-81
Preprint. Discussion started: 27 August 2021

Table 1. Soil properties in agricultural topsoils for the complete dataset and defined group levels according to parent material, land use and soil texture class. Values are means ± SD.

	Dataset (n=199)	DCS (n= 50)	LBS (n=50)	DLS (n=50)	PSS (n=49)	Sandy soils (n=54)	Loamy soils (n=98)	Silty soils (n=42)	Arable (n=150)	Grassland (n=49)
SOC [%]	1.94 ± 0.87	3.03 ± 0.78	1.61 ± 0.39	1.92 ± 0.49	1.17 ± 0.33	1.41 ± 0.45	2.08 ± 0.87	2.08 ± 0.76	1.82 ± 0.73	2.29 ± 1.11
Nitrogen [%]	0.20 ± 0 10	0.33 ± 0.08	0.14 ± 0.03	0.19 ± 0.04	0.13 ± 0.04	0.13 ± 0.03	0.22 ± 0.10	0.21 ± 0.08	0.19 ± 0.08	0.23 ± 0.12
Hydrogen [%]	0.56 ± 0.29	0.94 ± 0.25	0.33 ± 0.07	0.59 ± 0.15	0.38 ± 0.12	0.33 ± 0.08	0.64 ± 0.31	0.63 ± 0.22	0.57 ± 0.29	0.54 ± 0.27
Oxygen [%]	3.77 ± 1.93	6.15 ± 0.97	2.45 ± 0.63	3.87 ± 2.00	2.56 ± 0.70	2.18 ± 0.53	4.23 ± 1.63	4.67 ± 2.46	3.62 ± 1.82	4.24 ± 2.14
HWEC [µg/g]	753 ± 322	1071 ± 353	661 ± 163	732 ± 214	545 ± 252	570 ± 199	813 ± 319	782 ± 276	669 ± 231	1010 ± 410
HWEN [µg/g]	99.4 ± 42.0	130 ±35.5	78.9 ± 28.2	107 ± 37.2	80.4 ± 43.8	70.4 ± 31.0	106 ± 39.9	116 ± 40.3	93.8 ± 39.9	116 ± 43.5
MBC [µg/g]	247 ± 143	325 ± 159	130 ± 42.1	320 ± 118	209 ± 117	123 ± 47.2	271 ± 132	322 ± 119	205 ± 93.0	377 ± 186
MBN [µg/g]	41.2 ± 23.5	53.5 ± 25.3	22.6 ± 8.78	50.8 ± 23.2	37.1 ± 17.7	22.9 ± 10.2	44.5 ± 22.1	52.3 ± 21.7	35.5 ± 18.3	58.5 ± 28.5
Respiration [µg CO_2-C_g d-m- h]	0.26 ± 0.11	0.29 ± 0.11	0.21 ± 0.05	0.30 ± 0.12	0.22 ± 0.10	0.20 ± 0.07	0.27 ± 0.11	0.28 ± 0.10	0.23 ± 0.09	0.32 ± 0.13
MBC/SOC	1.36 ± 0.71	1.05 ± 0.31	0.89 ± 0.61	1.75 ± 0.72	1.73 ± 0.62	0.97 ± 0.51	1.42 ± 0.67	1.71 ± 0.82	1.23 ± 0.66	1.74 ± 0.70
SOC/N	11.7 ± 2.13	10.5 ± 0.98	13.7 ± 2.20	11.9 ± 2.11	10.7 ± 1.25	12.9 ± 2.58	11.1 ± 1.55	11.5 ± 2.06	11.6 ± 2.24	12.0 ± 1.76
HWE-C/N	9.90 ± 4.98	9.76 ± 2.33	11.1 ± 5.02	8.60 ± 2.85	10.2 ± 7.61	11.64 ± 6.77	9.66 ± 4.45	8.20 ± 2.15	9.80 ± 5.64	13.3 ± 6.40
MB-C/N	7.41 ± 2.57	7.62 ± 2.66	7.54 ± 3.36	7.83 ± 2.00	6.66 ± 1.81	7.02 ± 3.17	7.57 ± 2.44	7.55 ± 2.01	7.36 ± 2.79	7.55 ± 1.68
IC [%]	0.37 ± 1.18	-	-	1.43 ± 1.98	-	-	0.12 ± 0.62	1.36 ± 2.04	0.39 ± 1.24	0.29 ± 0.98
pH	4.98 ± 0.89	4.78 ± 0.61	4.70 ± 0.72	5.89 ± 0.77	5.47 ± 0.57	4.79 ± 0.73	5.02 ± 0.76	5.46 ± 0.90	5.02 ± 0.87	4.88 ± 0.87
ECEC [mmolc/kg]	65.6 ± 29.2	66.8 ± 21.0	38.8 ± 14.4	96.7 ± 26.3	58.6 ± 15.2	40.1 ± 12.9	66.6 ± 21.6	94.7 ± 28.5	65.6 ± 28.6	65.5± 31.1
Ca + Mg_{ECEC} [mmolc/kg]	55.7 ± 28.5	54.2 ± 21.2	30.8 ± 14.3	86.4 ± 26.6	50.0 ± 13.6	32.4 ± 12.9	55.5 ± 21.1	84.9 ± 28.5	54.9 ± 27.6	58.3 ± 31.0
Fe_o [g/kg]	2.34 ± 1.18	3.95 ± 0.72	1.40 ± 0.40	2.24 ± 0.80	1.77 ± 0.66	1.32 ± 0.32	2.69 ± 1.12	2.66 ± 1.05	2.30 ± 1.14	2.49 ± 1.27
Fe_d-Fe_o [g/kg]	4.57 ± 2.18	6.92 ± 2.00	3.27 ± 1.18	4.50 ± 1.48	3.54 ± 1.74	2.91 ± 1.15	5.22 ± 2.20	5.10 ± 2.04	4.67 ± 2.23	4.27 ± 1.97
Al_o [g/kg]	1.26 ± 1.13	2.98 ± 0.89	0.84 ± 0.44	0.62 ± 0.30	0.61 ± 0.21	0.77 ± 0.45	1.53 ± 1.25	1.10 ± 0.98	1.21 ± 1.07	1.42 ± 1.28
Sand [%]	44.2 ± 23.1	26.8 ± 5.80	69.1 ± 17.9	24.6 ± 8.71	57.6 ± 13.5	75.1 ± 10.8	38.4 ± 13.5	21.0 ± 5.09	44.8 ± 23.8	42.3 ± 20.9
cSilt+ mSilt [%]	29.1 ± 13.3	30.8 ± 4.53	17.6 ± 13.6	43.7 ± 6.67	23.4 ± 7.97	13.5 ± 8.39	30.5 ± 7.11	45.1 ± 6.59	28.8 ± 13.5	29.9 ± 12.8
fSilt + clay [%]	26.8 ± 12.7	42.4 ± 4.95	13.2 ± 4.75	31.7 ± 5.74	19.0 ± 7.01	11.5 ± 3.22	31.1 ± 10.6	33.9 ± 6.67	26.4 ± 13.0	27.8 ± 11.7
Stones [%]	14.3 ± 12.3	29.3 ± 8.91	6.70 ± 6.51	13.1 ± 8.99	7.59 ± 8.29	6.88 ± 4.52	18.0 ± 14.0	14.5 ± 10.1	15.0 ± 12.7	11.9 ± 10.7

https://doi.org/10.5194/soil-2021-81
Preprint. Discussion started: 27 August 2021

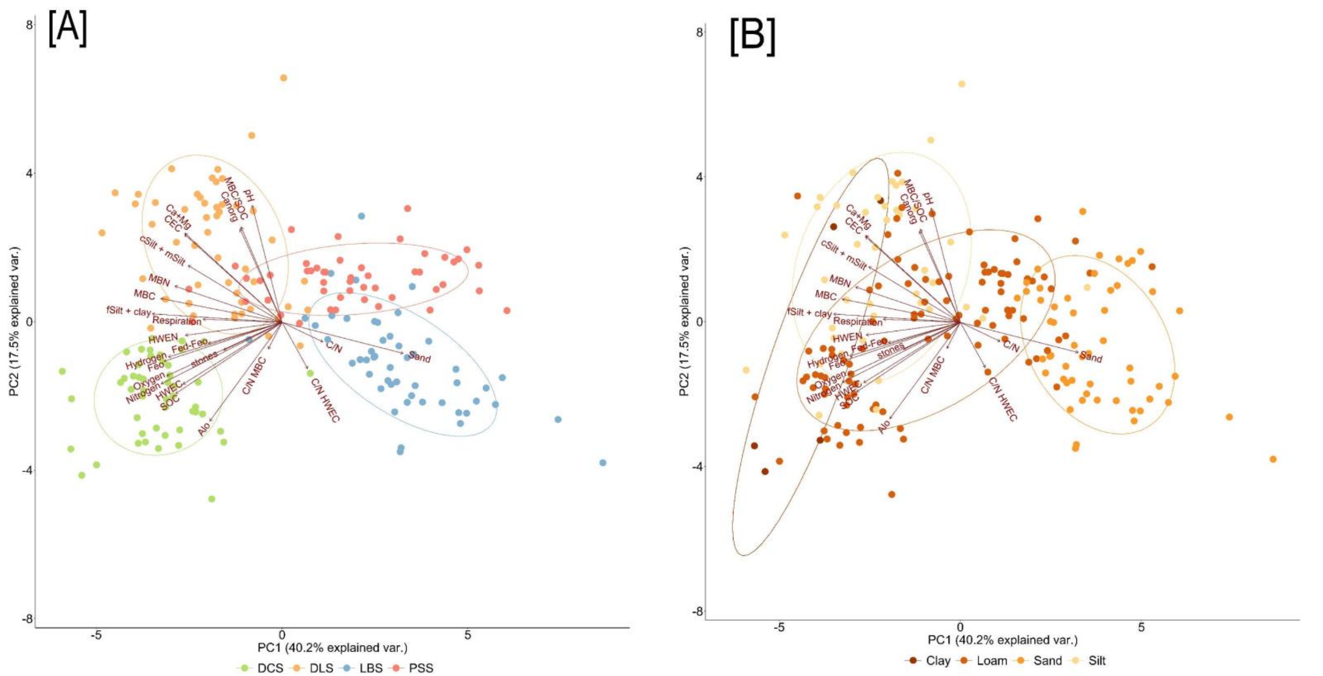
3 Results

The dataset covers soils and topsoil properties with broad ranges of 24 parameters and parameter ratios, respectively, of SOM, soil mineral phase and microbial biomass (Table 1). For example, soil pH ranged from very strongly acidic (pH 3.8) to slightly alkaline (pH 7.4); soil texture varied from sandy to clayey texture. Thereby, parent materials essentially influenced characteristics of the mineral phase related parameters such as texture, e.g. soils developed from sandy parent material such as LBS had a sandy texture with sand content of up to 91.9 %. Soils developed from DCS and DLS parent material had elevated contents of fine silt plus clay (33.4-53.3% and 16.7-44.8, respectively). Additionally, high contents of pedogenic oxides were found in soils from DCS while ECEC and especially the contents of the polyvalent cations $(Ca+Mg)_{ECEC}$ were high in soils developed from DLS (Table 1). Higher contents of SOC, HWEC and MBC were found for all parent material substrates in grassland soils compared to arable soils (Table 1 and SI Table A). For the entire dataset, SOC ranged from 0.38 to 5.32 %, while ranges from 237 to 1889 µg/g and 52.4 to 810 µg/g were determined for HWEC and MBC, respectively. SOC was strongly correlated with HWEC ($R^2 = 0.75$) while the correlation with MBC was substantially lower ($R^2 = 0.40$). The dissimilar correlations of SOC with the two labile fractions indicate differences between HWEC and MBC, which was further confirmed by the mediocre correlation between HWEC and MBC ($R^2 = 0.55$).

To identify possible local clusters due to different sampling sites, parent material or land use systems within the dataset, PCA was conducted including all 24 soil parameters and parameter ratios (Fig. 2). Principal component (PC) 1 to 3 explained 65 % of the variance and had eigenvalues > 1 (Table 2). Parameters related to the soil mineral phase loaded on all three PCs. Additionally, highest loadings on PC 1 were found for parameters describing the composition of SOM. For PC 2 high loadings were further found for parameters related to soil acidity (pH, IC, ECEC, $(Ca+Mg)_{ECEC}$) as well as for SOC and the microbial ratio MBC/SOC. The HWEC and respiration further loaded on PC 3 (Table 2). A plot of the first two PCs shows clear clusters that were strongly related to the parent materials according to the different sampling sites (Fig. 2 A). In addition, samples clustered somewhat different when assigned to different soil texture classes (Fig. 2 B). Land use, however, was insufficient to explain separation into different local clusters (Fig. S1**)**. Instead, it could be used as a global cluster covering soils with separated effects due to land use management. Compared to the entire dataset, the identified clusters based on parent material and soil texture showed distinct properties of the SOM and the mineral phase (Table 1). In contrast to the local clusters, the global cluster according to land use classes showed mostly properties quite similar to the entire dataset. Overall, identified clusters strongly depended on the composition of SOM as well as on specific properties of the soil mineral phase, e.g. texture or soil pH related properties. With a smaller relevance, parameters regarding the characteristics of soil microorganisms separated the dataset into clusters (Table 2).

https://doi.org/10.5194/soil-2021-81
Preprint. Discussion started: 27 August 2021

Fig. 2. Principal components 1 and 2 with loadings of the variables indicating the clustering of the dataset according to parent material [A] and soil texture [B]. Parent materials are Devonian clay schist (DCS), sandy dolomitic limestone (DLS), Luxemburg sandstone (LBS), and Permian siltstone and fine sandstone (PSS).



https://doi.org/10.5194/soil-2021-81
Preprint. Discussion started: 27 August 2021

201 **Table 2.** Loadings of the variables on the first three principal components.

202

	PC1	PC2	PC3
SOC	-0.24	-0.24	-0.19
Nitrogen	-0.27	-0.21	-0.04
Hydrogen	-0.26	-0.12	0.17
Oxygen	-0.26	-0.18	0.07
HWEC	-0.22	-0.21	-0.36
HWEN	-0.22	-0.04	-0.19
MBC	-0.27	0.08	-0.26
MBN	-0.24	0.12	-0.26
Respiration	-0.18	0.01	-0.36
MBC/SOC	-0.09	0.33	-0.12
C/N SOM	0.09	-0.07	-0.36
C/N HWEC	0.06	-0.16	-0.13
C/N MB	-0.03	-0.09	0.04
IC	-0.09	0.32	-0.09
pH	-0.07	0.4	0.03
ECEC	-0.22	0.3	0.07
$(Ca+Mg)_{ECEC}$	-0.22	0.3	0.06
Feo	-0.27	-0.13	0.12
Fed-Feo	-0.17	-0.07	0.37
Alo	-0.16	-0.34	0.14
Sand	0.27	-0.11	-0.11
cSilt + mSilt	-0.21	0.19	0.12
fSilt + clay	-0.29	0.03	0.18
Stones	-0.13	-0.09	0.29
Proportion of Variance	40.2	17.5	7.47
Cumulative Proportion	40.2	57.8	65.23
Eigenvalue	9.66	4.21	1.79

203

204

https://doi.org/10.5194/soil-2021-81
Preprint. Discussion started: 27 August 2021

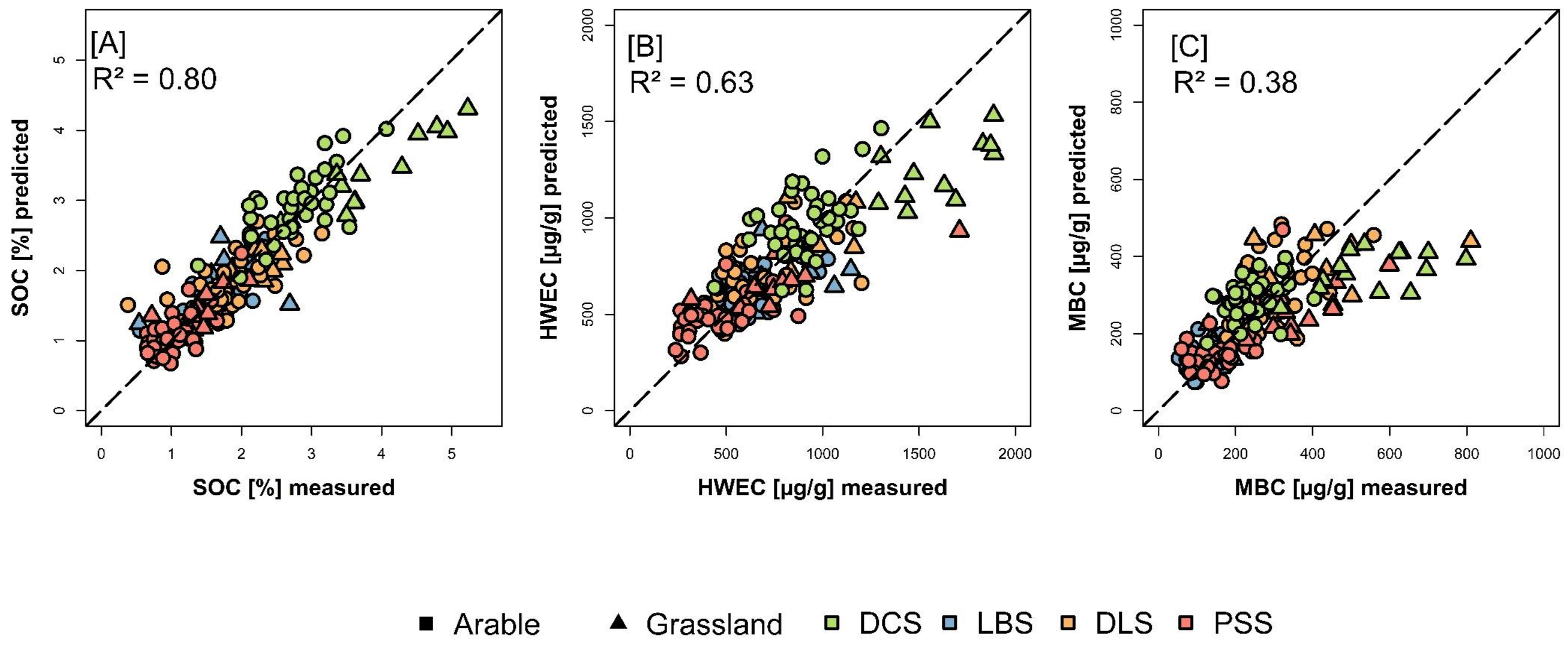
In order to test whether single parameters are suitable predictors of SOC, HWEC and MBC ten independent parameters describing the properties of the soil mineral phase were selected from the dataset (Table 1). Regressions were calculated based on the total dataset (n = 199), for further global clusters (e.g. arable or grassland soils) and the local clusters that were identified in PCA, i.e. subgroups based on the four parent rock materials and major texture classes (Table 3). Using the complete dataset, highly significant regressions of SOC, HWEC and MBC to most soil mineral phase parameters were found, yet predominantly at a low level of explained variance (Table 3). Compared to the complete dataset substantially different soil parameters explained SOC, HWEC and MBC especially for smaller clusters such as soils from the parent materials DCS or LBS. Yet, clusters comprising large sample numbers, where soil parameters cover broad ranges such as the clusters of loamy, arable or grassland soils, showed significantly contributing parameters that largely matched with those found for the complete dataset. All clusters differed in their pattern of significant parameters. However, for the complete dataset as well as for the clusters the explained variance decreased from SOC to the labile fractions HWEC and MBC (Fig. 3 and Table 3). Only some properties such as sand. ECEC or $(Ca+Mg)_{ECEC}$ showed for MBC a higher explained variance compared to SOC and HWEC (Table 3). For the entire dataset the content of SOC was best explained by Al_o and Fe_o as predictor parameter (R^2 = 0.63 and 0.56, respectively) while soil texture related properties such as sand or fSilt plus clay explained SOC on a lower level (Table 3). Other determined mineral phase parameters such as cSilt plus mSilt or ECEC explained variance to a negligible extent (Table 3). With lower values for R^2, HWEC was explained by similar soil mineral phase parameters, as it was the case for SOC. With R^2 of 0.39 and a variance of 0.38 HWEC was best explained by pedogenic oxides (Fe_o and Al_o, Table 3). In contrast, the predictors for MBC were quite distinct. Especially parameters related to soil texture such as fSilt plus clay (R^2 = 0.43) or sand (R^2 = 0.45) better explained the variance of MBC compared to HWEC (R^2 = 0.27 and 0.16, respectively). Nevertheless, none of the applied parameters could explain in all cases the complete variance of SOC, HWEC or MBC to a sufficient extent. Explained variance of SOC and its labile fractions varied strongly between the parent material clusters. In general, the variance in these clusters was explained to a substantially lower extent compared to the whole dataset (Table 3). In most cases, parameters of soil texture and pedogenic oxides correlated significantly with SOC, HWEC and MBC. Additional to these parameters, $(Ca+Mg)_{ECEC}$ was useful to predict SOC and MBC for some parent material clusters (Table 3). Highest values of R^2 were reached for the regression between SOC and Al_o and Fe_o (0.47, 0.42) in the cluster DCS and fSilt plus clay (0.37) in the cluster PSS. R^2 was even lower in the clusters LBS and DLS with maximum values of 0.21 and 0.20 respectively. Further, the cluster of loamy soils was also best described by parameters representing pedogenic oxides and texture. Much lower R^2 were found for the sandy and silty soil clusters with Al_o and texture parameters (sandy) and additionally Fe_o (silty) as best descriptors. While for SOC, HWEC and MBC mostly the same descriptors were found (yet on different level of R^2), they were partially different for MBC of the clusters silty and loamy soils.

https://doi.org/10.5194/soil-2021-81
Preprint. Discussion started: 27 August 2021

Table 3. Linear regression coefficient R^2 for parameters explaining the variance of SOC [%], HWEC and MBC [µg kg^{-1}] respectively, for soils groups of different parent material, major textural class and land use

		Fe_o [g kg^{-1}]	Fe_d-Fe_o [g kg^{-1}]	Al_o [g kg^{-1}]	Sand [%]	cSilt + mSilt [%]	fSilt + clay [%]	Stones [%]	ECEC [mmolc kg^{-1}]	$(Ca+Mg)_{ECEC}$ [mmolc kg^{-1}]	pH
						All samples					
Dataset n = 199	SOC	0.56***	0.16***	0.58***	0.23***	0.04**	0.46***	0.24***	0.07***	0.05**	0.02
	HWEC	0.39***	0.05**	0.38***	0.16***	0.04**	0.27***	0.11***	0.03*	0.02*	0.06***
	MBC	0.29***	0.07***	0.10***	0.45***	0.29**	0.43***	0.06***	0.29***	0.28***	0.04**
						Land use					
Arable n = 150	SOC	0.51***	0.25***	0.61***	0.23***	0.05**	0.46***	0.29***	0.09***	0.05**	0.02
	HWEC	0.37***	0.11***	0.37***	0.18***	0.06**	0.28***	0.17***	0.08***	0.04*	0.03*
	MBC	0.25***	0.15***	0.06**	0.64***	0.52***	0.51***	0.12***	0.61***	0.53***	0.21***
Grassland n = 49	SOC	0.73***	0.08*	0.73***	0.25***	0.02	0.59***	0.44***	0.04	0.04	0.00
	HWEC	0.67***	0.03	0.59***	0.21***	0.02	0.47***	0.30***	0.00	0.00	0.05
	MBC	0.54***	0.07	0.24***	0.41***	0.13**	0.67***	0.15**	0.11*	0.11*	0.00
						Parent material					
DCS n = 50	SOC	0.42***	0.25***	0.47***	0.00	0.04	0.03	0.00	0.00	0.00	0.02
	HWEC	0.17**	0.24***	0.17**	0.00	0.01	0.00	0.03	0.00	0.00	0.04
	MBC	0.14**	0.18**	0.06	0.00	0.03	0.01	0.06	0.00	0.00	0.01
LBS n = 50	SOC	0.01	0.11*	0.18**	0.11*	0.11*	0.08*	0.00	0.10*	0.11*	0.10*
	HWEC	0.03	0.03	0.06	0.01	0.01	0.01	0.00	0.05	0.04	0.00
	MBC	0.16**	0.04	0.00	0.21***	0.19**	0.21***	0.00	0.20**	0.17**	0.06
DLS n = 50	SOC	0.03	0.03	0.00	0.02	0.00	0.08*	0.20**	0.20**	0.20**	0.03
	HWEC	0.07	0.05	0.00	0.00	0.00	0.00	0.06	0.04	0.04	0.02
	MBC	0.02	0.00	0.03	0.05	0.00	0.11*	0.08*	0.19**	0.19**	0.06
PSS n = 49	SOC	0.35***	0.00	0.28***	0.36***	0.23***	0.37***	0.04	0.30***	0.27***	0.02
	HWEC	0.20**	0.03	0.21***	0.30***	0.29***	0.20**	0.12*	0.10*	0.09*	0.08*
	MBC	0.15**	0.00	0.28***	0.44***	0.37***	0.35***	0.02	0.16**	0.17**	0.10*
						Texture					
Sandy n = 54	SOC	0.00	0.01	0.40***	0.18**	0.19***	0.07	0.01	0.02	0.02	0.04
	HWEC	0.00	0.06	0.29***	0.08*	0.06	0.08*	0.03	0.03	0.04	0.11*
	MBC	0.13**	0.08*	0.04	0.08*	0.12*	0.00	0.00	0.07	0.05	0.01
Silty n = 42	SOC	0.25***	0.02	0.33***	0.01	0.22***	0.27***	0.00	0.03	0.03	0.01
	HWEC	0.20**	0.00	0.12*	0.00	0.08	0.08	0.04	0.01	0.02	0.04
	MBC	0.01	0.06	0.00	0.16**	0.00	0.07	0.05	0.17**	0.19**	0.06
Loamy n = 89	SOC	0.63***	0.16***	0.70***	0.41***	0.01	0.56***	0.36***	0.04*	0.02	0.10**
	HWEC	0.36***	0.02	0.36***	0.20***	0.01	0.24***	0.13***	0.00	0.00	0.15***
	MBC	0.08**	0.00	0.04*	0.12***	0.02	0.13***	0.00	0.14***	0.15***	0.00

Fig. 3. Predicted vs. measured content of SOC [A], HWEC [B] and MBC [C] for the global (complete) dataset. Parent materials are Devonian clay schist (DCS), sandy dolomitic limestone (DLS), Luxemburg sandstone (LBS), and Permian siltstone and fine sandstone (PSS).



https://doi.org/10.5194/soil-2021-81
Preprint. Discussion started: 27 August 2021

Comprising soils from all identified clusters, the set of descriptor parameters of the land use clusters were comparable to those of the global dataset. Yet, the variance of SOC and its labile fractions were explained to a much higher extent for the global dataset and the clusters of arable soils and especially grassland soils compared to the clusters based on parent material and texture. Both land use types include an equal weight of samples from each parent material and act therefore as global cluster. While SOC was explained by complex interactions of several different parameters for the distinct fractions, less variables showed a significant contribution to explain the variability of HWEC and MBC.

Since bivariate linear models insufficiently explained SOC, HWEC and MBC, respectively, mixed effect models were developed. In these models, mineral phase parameters were applied as fixed effects, and land use, parent material and texture were used as random effects (Table 4, Fig. 4 and Fig. 5). Variability of SOC, HWEC and MBC were much better explained than by linear regressions indicating that organic matter depends on complex interactions of several components of the mineral phase. In general, mixed effect models explained variance in the order SOC > HWEC > MBC (Fig. 3 and Table 4). Measured and predicted data using the mixed effect models showed a close relationship along the 1:1 prediction line while scatter increased at higher contents of HWEC and especially of MBC, showing that estimates for grassland soils were inferior. Anyhow, correlations between measured data and predictions of the mixed effect models ($R^2 = 0.29$-0.91) were mostly higher than for bivariate linear regressions ($R^2 = 0.00 – 0.73$). Independent from the applied random effect, precision of prediction results increased with sample number and data range of parameters, respectively. Consequently, best model performance was achieved for the complete dataset as well as for some of the local clusters (e.g. DCS, loamy soils), while models for other local clusters such as LBS, DLS or sandy soils revealed the poorest estimates of SOC (Table 4). In general, applying random effects such as parent material, land use or texture for mixed effect models led to distinct results for the prediction of SOC, HWEC or MBC (Table 4). For clusters according to land use variance was explained to a high extent (mean R^2 of 0.68 and 0.80 for cluster of arable and grassland respectively). Models using parent material or texture as random effect mostly showed minor differences for predictions of SOC, HWEC or MBC. Models using land use as random effect were partly distinct, though, indicating the different influence of land use on SOC and its labile fractions (Table 4).

https://doi.org/10.5194/soil-2021-81
Preprint. Discussion started: 27 August 2021

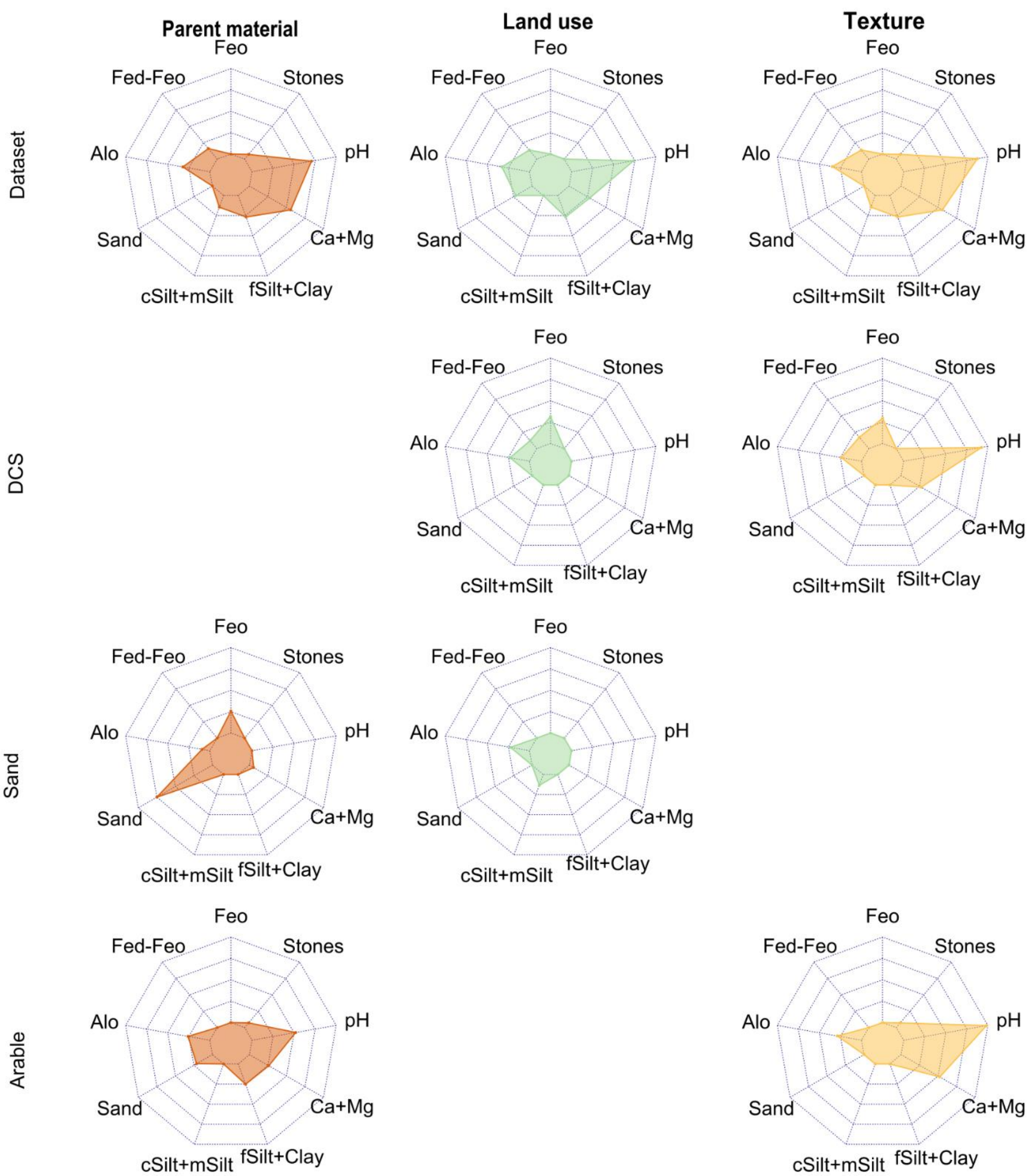
Table 4. R^2 of the models for prediction of SOC, HWEC, and MBC based on the results of mixed effect models.

	Parent material^{+}			Land use^{+}			Texture^{+}			Mean model prediction for cluster
Sample subgroups	SOC	HWEC	MBC	SOC	HWEC	MBC	SOC	HWEC	MBC	R^2
Dataset	0.80*	0.63*	0.38*	0.77*	0.66*	0.67*	0.77*	0.61*	0.40*	0.61
Land use										
Arable	0.80*	0.59*	0.70*				0.73*	0.53*	0.70*	0.68
Grassland	0.91*	0.75*	0.75*				0.89*	0.75*	0.75*	0.80
Parent material										
DCS	-	-	-	0.81*	0.78*	0.79*	0.73*	0.60*	0.56*	0.71
LBS	-	-	-	0.41*	0.34*	0.48*	0.41*	0.29*	0.30*	0.37
DLS	-	-	-	0.50*	0.35*	0.32*	0.50*	0.35*	0.25*	0.38
PSS	-	-	-	0.60*	0.55*	0.71*	0.63*	0.55*	0.61*	0.61
Texture										
Sandy soils	0.79*	0.61*	0.33*	0.54*	0.50*	0.54*	-	-	-	0.55
Silty soils	0.72*	0.75*	0.48*	0.72*	0.64*	0.48*	-	-	-	0.63
Loamy soils	0.84*	0.59*	0.40*	0.81*	0.64*	0.60*	-	-	-	0.65
Mean model prediction										
R^2	0.81	0.65	0.51	0.65	0.56	0.57	0.65	0.53	0.51	

+Applied random effect; ˜Not all random effects could applied to this group of clusters because of missing factor levels. *Significant on a level of <0.05

https://doi.org/10.5194/soil-2021-81
Preprint. Discussion started: 27 August 2021

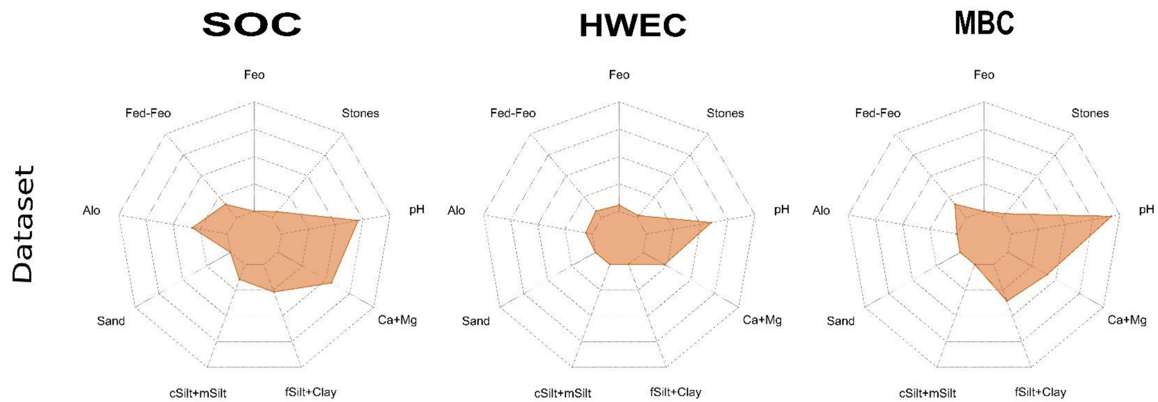
266 **Fig. 4.** Coefficients of the mixed effect models to predict SOC, multiplied with the mean values of the specific cluster indicating
267 the impact of the applied variables. Differentiation into clusters and used random factors. Variables are scaled from 0 to 1.



268
269

https://doi.org/10.5194/soil-2021-81
Preprint. Discussion started: 27 August 2021

Fig. 5. Comparison of the coefficient impact for mixed effect models to predict SOC, HWEC and MBC for the entire dataset by using parent material as random factor. Variables are scaled from 0 to 1.



https://doi.org/10.5194/soil-2021-81
Preprint. Discussion started: 27 August 2021

The different mixed effects models particularly comprised variables (Fig. 4, Fig. 5) that also proved significant in linear regressions (Table 3). Mineral phase parameters contributed with different significance to the models for SOC, HWEC and MBC. The SOC and HWEC were primarily explained by pedogenic oxides followed by soil texture related parameters. Not last, soil acidity indicated by pH and $(Ca+Mg)_{ECEC}$ was also relevant. MBC, compared to SOC or HWEC, was better explained by parameters linked to soil texture. Contribution of the variables, on SOC and its labile fraction was visualized using the mean values multiplied with their coefficients (Fig. 4, Fig 5). Distinct significant parameter combinations explaining SOC, HWEC and MBC were also found between the global data set and local clusters (Table 3,Fig. 4 and Fig. 5, SI Table 2). For example, within the soil texture related clusters pedogenic oxides, $(Ca+Mg)_{ECEC}$, pH and texture parameters were relevant to estimate SOC, HWEC and MBC. Regarding the random effects, applied mixed effect models using parent material as random effect explained variability of SOC best. For MBC and HWEC, however, best model fits were mostly obtained with land use as random effect. Only estimates of HWEC for the texture clusters were better when parent material was used as random effect.

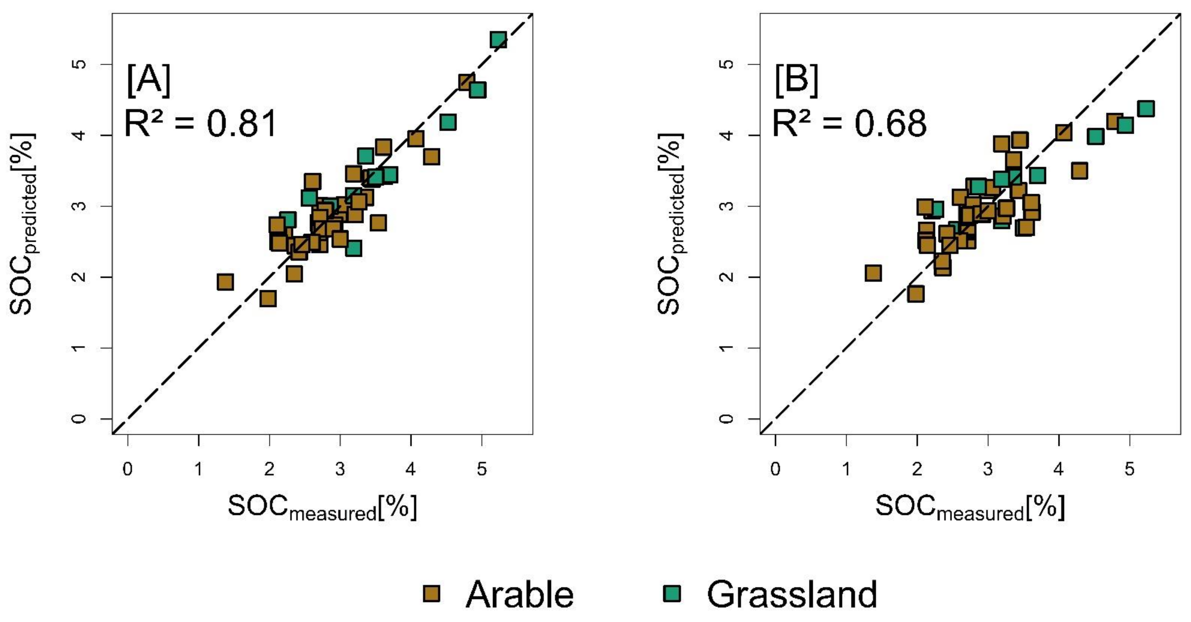
The R^2 of model predictions was best for the global clusters tested in this study, i.e. all data and data clustered according to arable or grassland land use. Yet, this was at least partly due to a larger sample size and a broader range of parameter values compared to the various local clusters. Applying the global model for SOC estimation to a smaller local cluster data set clearly revealed an inferior performance of the global compared to the local model (Fig. 6). The better performance of specific local models and parameter combinations was also found for other local clusters (Table 5 and SI Table 3)

Table 5. R^2 for implementation of the global dataset to local clusters to estimate SOC.

	SOC					
	Parent material		Land use		Texture	
Sample subgroups	Model	Global model to local cluster	Model	Global model to local cluster	Model	Global model to local cluster
Dataset	0.80		0.77		0.77	
DCS	-		0.81	0.68	0.73	0.65
LBS	-		0.41	0.23	0.41	0.24
DLS	-		0.50	0.30	0.50	0.35
PSS	-		0.60	0.57	0.63	0.57
Sandy soils	0.79	0.68	0.54	0.38	-	
Silty soils	0.72	0.65	0.72	0.60	-	
Loamy soils	0.84	0.83	0.81	0.79	-	
Arable	0.80	0.80			0.73	0.73
Grassland	0.91	0.87			0.89	0.87

https://doi.org/10.5194/soil-2021-81
Preprint. Discussion started: 27 August 2021

Fig. 6. Predicted vs. measured content of SOC of soil samples from the DCS cluster; predictions based on the local model [A] and the global model [B].



4 Discussion

Our study showed that interactions of SOC with the mineral phase are highly relevant for the content of SOC as well as of its labile fractions HWEC and MBC in soils. High correlations of SOC to fSilt plus clay (Table 3) agree with reports on the relevance of organo-mineral associations for the stabilization of SOC and related to this the accumulation of the labile fraction HWEC and MBC (Lützow et al., 2006). Furthermore, sandy soils contained the lowest content of SOC while loamy and silty soils had an equally higher content of SOC (Table 1). This is typically expected and confirms numerous previous reports, e.g. Ludwig et al. (2003) and Vos et al. (2018). In contrast, a slightly positive effect of sand on SOC was found for the in total very sandy soils in the parent material cluster of LBS. This, however, is most likely a consequence of agricultural practice, with high manure application to the LBS soils in the sampled area. This was further confirmed by a factor of 1.2 higher ratios of SOC/N and HWEC/N as well as by a lower oxygen content of SOM compared to soils of the other parent material clusters (factor of 0.6; Table 1). Besides parameters directly related to soil texture, pedogenic Al- and Fe-oxides were found to be strong predictors of SOC in soils. Accordingly, Al- and Fe-oxides were shown to have a relevant influence on the sequestration and stabilization of SOC (Kaiser and Guggenberger, 2000; Lützow et al., 2006) as well as to have a high affinity to retain components of the labile SOC fractions (Kaiser and Zech, 1998; Kaiser et al., 2002). Although soil acidity strongly affects soil processes such as microbial activity and turnover that are relevant for SOC accumulation (Kemmitt et al., 2006), no clear correlation between pH and SOC or its labile fractions was found by linear regression. Yet, soil parameters that are strongly related to soil acidity, i.e. ECEC as well as the content of exchangeable polyvalent cations such as Ca^{2+} and Mg^{2+}, were suitable predictors for SOC and its labile fractions in this and previous studies (O'Brien et al., 2015; Rasmussen et al., 2018). This is causally explained by the stabilization of SOC in organo-mineral associations and the contribution of multivalent cation bridges (Ca^{2+} and Mg^{2+}) to it (Kaiser et al., 2012). The minor ability of ECEC and $(Ca+Mg)_{ECEC}$ and the higher ability of pedogenic oxides to explain variance of SOC and its labile fractions in this study (Table 3), corresponds to findings of Rasmussen et al. (2018). They found a prevalence of pedogenic oxides in humid areas with moderately acidic soils, while exchangeable Ca and clay prevealed in soils of dry climates with circumneutral to alkaline pH. Such a prevalence of parameters to predict SOC, HWEC or MBC demonstrates that it is preferred to use specific parameter sets when it is aimed to focus on local areas. The bivariate models revealed that the stone content had only a small impact on SOC, HWEC and MBC. Hence, a funnel effect of the stone content, by funneling more SOC into the remaining fine textured soil (Bornemann et al., 2011) was irrelevant. The combinations of factors and soil properties affecting SOC and SOC fractions, respectively, were dissimilar between the different local areas investigated in this study. The PCA revealed that differences according to parent material and soil texture were most relevant to separate the dataset into various local clusters based on different factors (Fig. 2 A and B; Table 2). At the same time, this illustrates the importance of the mineral composition (parent material) and grain size (soil texture) for the accumulation of SOC as well as its labile fractions HWEC and MBC. In contrast, land use was not useful for a separation into clusters. This was unexpected because typically topsoils under grassland have higher SOC contents compared to arable soils (Poeplau et al., 2020), which was largely confirmed for the samples investigated in this study (Table 1). This went along with differences in the composition of SOM (Table 1 and Table SI). However, data ranges of SOC, HWEC and MBC contents were largely overlapping and similarities even increased in PCA when further soil properties were included. Consequently, a broad scatter of the land use clusters was obtained by PCA, suggesting to treat the land use clusters as global datasets as well.

Several studies with large datasets covering national or continental scales, e.g. soil inventories, pointed out the relevance of combinations of multiple factors and parameters instead of using single predictors to estimate SOC or its labile fractions (Vos et al., 2018). Furthermore, local studies covering small areas with narrow ranges of soil properties often show weak bivariate relationships between SOC and components of the mineral phase or environmental factors (Jian-Bing et al., 2006; Liddle et al.,

https://doi.org/10.5194/soil-2021-81
Preprint. Discussion started: 27 August 2021

2020). Accordingly, models focused on specific local clusters and combined with multiple parameter sets were superior compared to the global model that was developed for the global (complete) dataset to estimate SOC, HWEC or MBC (Fig. 6). The different parameter combinations indicate that distinct properties of the mineral phase control SOC, HWEC and MBC in the soils of the different clusters.

Understanding SOC as continuum (Lehmann and Kleber, 2015) implies that accumulation of SOC is a multidimensional process with various interacting factors and soil properties, respectively. The substantially lower ability of bivariate models to estimate SOC compared to multiple parameter models confirmed this assumption. Accordingly, it was superior to use multiparameter mixed effect models to estimate SOC and the two labile fractions. Especially parameter combinations within the land use clusters gained a high-explained variance (Table 3, Table 4). A comparison with studies on regional or national scale (Vos et al., 2018; Mayer et al., 2019) suggests that the importance of factors such as land use, soil texture or parent material varies with the observed scale. Wiesmeier et al. (2019) reported that soil texture, land use and land management are relevant to explain SOC at all scales. On regional or larger scale, also environmental factors such as climate, geology, soil use, topography are relevant for SOC. Yet, at a local or smaller scale factors such as climate become less important, while parameters representing small-scale soil physico-chemical properties gain importance for explaining the variability of SOC. Thereby, different factor and parameter combinations were identified for the different local clusters by mixed effect modeling. The prevalence of a parameter for quantification of SOC can differ dependent on environmental factors (Rasmussen et al., 2018).

Consequently, the quality of the multiparameter models was further improved by the implementation of local specific random effects such as parent material or land use. Dependent on the random factors parent material, soil texture class and land use different parameter combinations explained SOC, HWEC or MBC (Fig. 4 and Fig. 5). For the global (complete) dataset, nearly all predictor parameters showed a significant contribution to the explanation of SOC. Most of these soil mineral phase parameters were also significant in linear regression. In contrast to the bivariate models, most mixed effect models revealed parameters related to soil acidity as significantly important to estimate SOC, HWEC and MBC. This highlights the importance of soil acidity on SOC dynamics due to its effects on the reactivity of the mineral phase and the activity of microorganisms (Hillel, 2004). In order to explain the variability of HWEC and MBC for the various local clusters, different combinations of mineral phase parameters were required that also clearly differed from the parameter combinations used in the models for SOC (Fig. 4 and Fig. 5). Such differences concerning significantly contributing parameters were also found by other studies for specific clusters or local sampling sites (Heinze et al., 2018; Quesada et al., 2020). This emphasizes that local models are required and superior when it is the aim to estimate SOC and SOC fractions on a local scale. The global models used for the global dataset in this study reached the best predictions for SOC, HWEC and MBC. Yet, this was largely biased by the large samples size; applying the same global models to local samples sets produced clearly poorer estimates compared to the more specific local models (Fig. 6; Table 4 and Table 5). Consequently, aggregation of smaller datasets, e.g. from a local scale, to a larger dataset enables to predict SOC and its labile fractions to a satisfying extent. In opposite a global dataset applied to the local area with defined properties is partially practicable, resulting in a variance explained on a lower level. Dependend on the properties of the soil mineral phase, each specific cluster was controlled by other properties, which best explain the accumulation of SOC and its labile fractions. This implies the importance for analysis of local clusters to avoid a subordination by models of global datasets.

Comparing the results of mixed effect models using the different random effects (parent material, soil texture, land use), the models using parent material yielded best results for the estimation of SOC. For HWEC and MBC best predictions at a sufficient quality level were obtained by models using land use as random effect (Table 4). The parent material predefines the boundaries for accumulation and stabilization of organic matter (Gray et al., 2015). The importance of land use as random effect especially

https://doi.org/10.5194/soil-2021-81
Preprint. Discussion started: 27 August 2021

for the labile fractions results from the fact that these are especially influenced by soil management (Cardoso et al., 2013; Lal, 2016).

In general, the variance explained by the mixed effect models was not similar, but varied between SOC and its labile fractions HWEC and MBC. It became clear that SOC and the labile fractions HWEC and MBC are not fully correlated but quantitatively quite distinct SOM pools with different annual dynamics (Wander, 2004; Tokarski et al., 2020). Not last, the faster turnover of the labile fractions is one of the reasons for the lower explained variability by the different models. HWEC is a measure of bioavailable and degradable organic carbon (Weigel et al., 1998). Although it is closely correlated to SOC (R^2 =0.75) it is best estimated by distinct parameter combinations compared to SOC, which is explained by the substantially higher variability of HWEC (Table 3 and 4). Changes in HWEC are mostly assigned to inputs of organic fertilizer substrates (Weigel et al., 1998) and the soil management (Ghani et al., 2003). For MBC especially soil management and factors such as C-input, climate, soil texture and soil pH are relevant (Wardle, 1992). Accordingly, the effect of land use but also of soil texture was most relevant for MBC accumulation. Similar to findings of Ludwig et al. (2015), MBC increased with the content of silt and clay but declined with sand, which is explained amongst other by the contribution of MBC to aggregate formation, the habitable surface and accessibility of SOC (Totsche et al., 2018). Additionally, management practices such as tillage and the application of organic fertilizer directly influence MBC (Liang et al., 1997).

5 Conclusions

The reliable estimation of SOC and of its labile fractions HWEC and MBC is a task of growing importance in order to manage soil properties and functioning. That task will most often focus on local soilscapes with minor variation range in soil properties. This study showed that local models are superior to global models. Mixed parameter models combined with random effects yielded best estimates and highest explained variance for SOC and even its labile and quite dynamic fractions HWEC and MBC. For this purpose, the application of multivariate approaches to estimate SOC, HWEC and MBC clearly outperforms models based on bivariate correlations. Even a reduced dataset, representing parameters of the soil mineral phase is suited to estimate contents of SOC as well as HWEC and MBC. The inclusion of overall factors such as parent material, soil texture class and land use as random effects further improves the models. Global models, developed from large-scale studies across countries or continents, often reach best estimates; however, they are subordinate for the above-mentioned small-scale areas and low sample numbers. From a practical perspective, the selected set of soil mineral phase parameters can be easily determined by using well-established methods and the parameters are rather stable over a longer-term. Thus, using such parameters for the sufficient estimation of SOC, HWEC and MBC is expedient. The presented research will be further enlarged by studying larger datasets containing more clusters in order to better identify local drivers of SOC and of its labile fractions.

6 Code/Data availability

The raw data is available upon request to the authors.

7. Author contribution

MO, TU, MV, STB conceived, and designed the study. MO, MS, SS performed the sampling and analysis. MO wrote the first draft. All authors (MO, MS, SS; UT, MV,STB) contributed to generating and and reviewing the subsequent versions of the manuscript.

8. Competing interests

The authors declare that there is no conflict of interest.

9 Acknowledgements

This study was founded by the German Environment Agency in the framework of the ScreeSOM project ("Screening methods for a cost effective detection of supply with SOM in arable and grassland soils", project no. 371 673 208 0). The authors thank the colleagues of the Soil Science Department of Trier University, P. Ziegler and E. Sieberger and the students A. Forens, M. Heinrich, K. Struwe and A. Hergert for assistance during field and laboratory work.

References

Adhikari, K., Mishra, U., Owens, P. R., Libohova, Z., Wills, S. A., Riley, W. J., Hoffman, F. M., and Smith, D. R.: Importance and strength of environmental controllers of soil organic carbon changes with scale, Geoderma, 375, 114472, https://doi.org/10.1016/j.geoderma.2020.114472, 2020.

Angst, G., Messinger, J., Greiner, M., Häusler, W., Hertel, D., Kirfel, K., Kögel-Knabner, I., Leuschner, C., Rethemeyer, J., and Mueller, C. W.: Soil organic carbon stocks in topsoil and subsoil controlled by parent material, carbon input in the rhizosphere, and microbial-derived compounds, Soil Biology and Biochemistry, 122, 19–30, https://doi.org/10.1016/j.soilbio.2018.03.026, 2018.

Arrouays, D., Saby, N., Walter, C., Lemercier, B., and Schvartz, C.: Relationships between particle-size distribution and organic carbon in French arable topsoils, Soil Use & Management, 22, 48–51, https://doi.org/10.1111/j.1475-2743.2006.00020.x, 2006.

Barré, P., Durand, H., Chenu, C., Meunier, P., Montagne, D., Castel, G., Billiou, D., Soucémarianadin, L., and Cécillon, L.: Geological control of soil organic carbon and nitrogen stocks at the landscape scale, Geoderma, 285, 50–56, https://doi.org/10.1016/j.geoderma.2016.09.029, 2017.

Blume, H.-P., Stahr, K., and Leinweber, P.: Bodenkundliches Praktikum: Eine Einführung in pedologisches Arbeiten für Ökologen, insbesondere Land- und Forstwirte, und für Geowissenschaftler, 3., neubearb. Aufl., Spektrum Akademischer Verlag, Heidelberg, 255 pp., 2011.

Bornemann, L., Herbst, M., Welp, G., Vereecken, H., and Amelung, W.: Rock Fragments Control Size and Saturation of Organic Carbon Pools in Agricultural Topsoil, Soil Science Society of America Journal, 75, 1898–1907, https://doi.org/10.2136/sssaj2010.0454, 2011.

Cardoso, E., Vasconcellos, R., Bini, D., Miyauchi, M., dos Santos, C., Alves, P., Paula, A. de, Nakatani, A., Pereira, J., and Nogueira, M.: Soil health: looking for suitable indicators. What should be considered to assess the effects of use and management on soil health? 2013, 70, 274–289, https://doi.org/10.1590/S0103-90162013000400009, 2013.

Dignac, M.-F., Derrien, D., Barré, P., Barot, S., Cécillon, L., Chenu, C., Chevallier, T., Freschet, G. T., Garnier, P., Guenet, B., Hedde, M., Klumpp, K., Lashermes, G., Maron, P.-A., Nunan, N., Roumet, C., and Basile-Doelsch, I.: Increasing soil carbon storage: mechanisms, effects of agricultural practices and proxies. A review, Agron. Sustain. Dev., 37, 351, https://doi.org/10.1007/s13593-017-0421-2, 2017.

Fox, J. and Weisberg, S.: An R companion to applied regression, Third edition, SAGE, Los Angeles, xxx, 577 pages, 2019.

https://doi.org/10.5194/soil-2021-81
Preprint. Discussion started: 27 August 2021

Ghani, A., Dexter, M., and Perrott, K.W.: Hot-water extractable carbon in soils: a sensitive measurement for determining impacts of fertilisation, grazing and cultivation, Soil Biology and Biochemistry, 35, 1231–1243, https://doi.org/10.1016/S0038-0717(03)00186-X, 2003.

Gray, J. M., Bishop, T. F.A., and Wilson, B. R.: Factors Controlling Soil Organic Carbon Stocks with Depth in Eastern Australia, Soil Science Society of America Journal, 79, 1741–1751, https://doi.org/10.2136/sssaj2015.06.0224, 2015.

Hassink, J., Bouwman, L. A., Zwart, K. B., Bloem, J., and Brussaard, L.: Relationships between soil texture, physical protection of organic matter, soil bioata, and C and N mineralization in grassland soils, Geoderma, 57, 105–128, https://doi.org/10.1016/0016-7061(93)90150-J, 1993.

Heimann, M. and Reichstein, M.: Terrestrial ecosystem carbon dynamics and climate feedbacks, Nature, 451, 289–292, https://doi.org/10.1038/nature06591, 2008.

Heinemeyer, O., Insam, H., Kaiser, E. A., and Walenzik, G.: Soil microbial biomass and respiration measurements: An automated technique based on infra-red gas analysis, Plant and Soil, 116, 191–195, https://doi.org/10.1007/BF02214547, 1989.

Heinze, S., Ludwig, B., Piepho, H.-P., Mikutta, R., Don, A., Wordell-Dietrich, P., Helfrich, M., Hertel, D., Leuschner, C., Kirfel, K., Kandeler, E., Preusser, S., Guggenberger, G., Leinemann, T., and Marschner, B.: Factors controlling the variability of organic matter in the top- and subsoil of a sandy Dystric Cambisol under beech forest, Geoderma, 311, 37–44, https://doi.org/10.1016/j.geoderma.2017.09.028, 2018.

Heller, C. and Zeitz, J.: Stability of soil organic matter in two northeastern German fen soils: the influence of site and soil development, J Soils Sediments, 12, 1231–1240, https://doi.org/10.1007/s11368-012-0500-6, 2012.

Herold, N., Schöning, I., Michalzik, B., Trumbore, S., and Schrumpf, M.: Controls on soil carbon storage and turnover in German landscapes, Biogeochemistry, 119, 435–451, https://doi.org/10.1007/s10533-014-9978-x, 2014.

Hillel, D.: Encyclopedia of soils in the environment, Elsevier/Academic Press, Oxford UK, Boston, 4 v, 2004.

Hobley, E., Wilson, B., Wilkie, A., Gray, J., and Koen, T.: Drivers of soil organic carbon storage and vertical distribution in Eastern Australia, Plant Soil, 390, 111–127, https://doi.org/10.1007/s11104-015-2380-1, 2015.

Jenny, H.: Factors of soil formation: A system of quantitative pedology, McGraw-Hill, New York, 1941.

Jian-Bing, W., Du-Ning, X., Xing-Yi, Z., Xiu-Zhen, L., and Xiao-Yu, L.: Spatial Variability of Soil Organic Carbon in Relation to Environmental Factors of a Typical Small Watershed in the Black Soil Region, Northeast China, Environ Monit Assess, 121, 597–613, https://doi.org/10.1007/s10661-005-9158-5, 2006.

Joergensen, R. G.: The fumigation-extraction method to estimate soil microbial biomass: calibration of the kEC value, Soil Biol. Biochem., 28, 25–31, https://doi.org/10.1016/0038-0717(95)00102-6, 1996.

Joergensen, R. G.: The Fumigation-Extraction Method to Estimate Soil Microbial Biomass: Extraction with 0.01 M CaCl2, Agribiol Res, 48, 319-324, 1995.

Joergensen, R. G. and Mueller, T.: The fumigation-extraction method to estimate soil microbial biomass: calibration of the kEN value, Soil Biol. Biochem., 28, 33–37, https://doi.org/10.1016/0038-0717(95)00101-8, 1996.

Kaiser, K. and Guggenberger, G.: The role of DOM sorption to mineral surfaces in the preservation of organic matter in soils, Organic Geochemistry, 31, 711–725, https://doi.org/10.1016/S0146-6380(00)00046-2, 2000.

Kaiser, K. and Zech, W.: Soil Dissolved Organic Matter Sorption as Influenced by Organic and Sesquioxide Coatings and Sorbed Sulfate, Soil Science Society of America Journal, 62, 129–136, https://doi.org/10.2136/sssaj1998.03615995006200010017x, 1998.

https://doi.org/10.5194/soil-2021-81
Preprint. Discussion started: 27 August 2021

Kaiser, K., Eusterhues, K., Rumpel, C., Guggenberger, G., and Kögel-Knabner, I.: Stabilization of organic matter by soil minerals - investigations of density and particle-size fractions from two acid forest soils, J. Plant Nutr. Soil Sci., 165, 451–459, https://doi.org/10.1002/1522-2624(200208)165:4<451:AID-JPLN451>3.0.CO;2-B, 2002.

Kaiser, M., Ellerbrock, R. H., Wulf, M., Dultz, S., Hierath, C., and Sommer, M.: The influence of mineral characteristics on organic matter content, composition, and stability of topsoils under long-term arable and forest land use, J. Geophys. Res., 117, G02018, https://doi.org/10.1029/2011JG001712, 2012.

Kemmitt, S., Wright, D., Goulding, K., and Jones, D.: pH regulation of carbon and nitrogen dynamics in two agricultural soils, Soil Biology and Biochemistry, 38, 898–911, https://doi.org/10.1016/j.soilbio.2005.08.006, 2006.

Kleber, M., Eusterhues, K., Keiluweit, M., Mikutta, C., Mikutta, R., and Nico, P. S.: Mineral–Organic Associations: Formation, Properties, and Relevance in Soil Environments, in: Advances in Agronomy, edited by: Donald L. Sparks, Elsevier, 1–140, https://doi.org/10.1016/bs.agron.2014.10.005, 2015.

Körschens, M., Schulz, E., and Behm, R.: Heißwasserlöslicher C und N im boden als kriterium für das N-Nachlieferungsvermögen, Zentralblatt für Mikrobiologie, 145, 305–311, https://doi.org/10.1016/S0232-4393(11)80045-4, 1990.

Lal, R.: Soil health and carbon management, Food Energy Secur, 5, 212–222, https://doi.org/10.1002/fes3.96, 2016.

Lehmann, J. and Kleber, M.: The contentious nature of soil organic matter, Nature, 528, 60–68, https://doi.org/10.1038/nature16069, 2015.

Liang, B. C., MacKenzie, A. F., Schnitzer, M., Monreal, C. M., Voroney, P. R., and Beyaert, R. P.: Management-induced change in labile soil organic matter under continuous corn in eastern Canadian soils, 26, 88–94, https://doi.org/10.1007/s003740050348, 1997.

Liang, C., Schimel, J. P., and Jastrow, J. D.: The importance of anabolism in microbial control over soil carbon storage, Nature microbiology, 2, 17105, https://doi.org/10.1038/nmicrobiol.2017.105, 2017.

Liddle, K., McGonigle, T., and Koiter, A.: Microbe Biomass in Relation to Organic Carbon and Clay in Soil, Soil Syst., 4, 41, https://doi.org/10.3390/soilsystems4030041, 2020.

Ludwig, B., John, B., Ellerbrock, R., Kaiser, M., and Flessa, H.: Stabilization of carbon from maize in a sandy soil in a long-term experiment, Eur J Soil Sci, 54, 117–126, https://doi.org/10.1046/j.1365-2389.2003.00496.x, 2003.

Ludwig, M., Achtenhagen, J., Miltner, A., Eckhardt, K.-U., Leinweber, P., Emmerling, C., and Thiele-Bruhn, S.: Microbial contribution to SOM quantity and quality in density fractions of temperate arable soils, Soil Biology and Biochemistry, 81, 311–322, https://doi.org/10.1016/j.soilbio.2014.12.002, 2015.

Lützow, M. v., Kogel-Knabner, I., Ekschmitt, K., Matzner, E., Guggenberger, G., Marschner, B., and Flessa, H.: Stabilization of organic matter in temperate soils: mechanisms and their relevance under different soil conditions - a review, Eur J Soil Science, 57, 426–445, https://doi.org/10.1111/j.1365-2389.2006.00809.x, 2006.

Lützow, M. von, Kögel-Knabner, I., Ekschmitt, K., Flessa, H., Guggenberger, G., Matzner, E., and Marschner, B.: SOM fractionation methods: Relevance to functional pools and to stabilization mechanisms, Soil Biology and Biochemistry, 39, 2183–2207, https://doi.org/10.1016/j.soilbio.2007.03.007, 2007.

Mayer, S., Kühnel, A., Burmeister, J., Kögel-Knabner, I., and Wiesmeier, M.: Controlling factors of organic carbon stocks in agricultural topsoils and subsoils of Bavaria, Soil and Tillage Research, 192, 22–32, https://doi.org/10.1016/j.still.2019.04.021, 2019.

Mehra, O. P. and Jackson, M. L.: Iron oxide removal from soils and clays by a dithionite citrate system buffered with sodium bicarbonate, Clays Clay Minerals, 7, 317–327, https://doi.org/10.1346/CCMN.1958.0070122, 1958.

https://doi.org/10.5194/soil-2021-81
Preprint. Discussion started: 27 August 2021

Mikutta, R., Kleber, M., Torn, M. S., and Jahn, R.: Stabilization of Soil Organic Matter: Association with Minerals or Chemical Recalcitrance?, Biogeochemistry, 77, 25–56, https://doi.org/10.1007/s10533-005-0712-6, 2006.

O'Brien, S. L., Jastrow, J. D., Grimley, D. A., and Gonzalez-Meler, M. A.: Edaphic controls on soil organic carbon stocks in restored grasslands, Geoderma, 251-252, 117–123, https://doi.org/10.1016/j.geoderma.2015.03.023, 2015.

Poeplau, C. and Don, A.: Sensitivity of soil organic carbon stocks and fractions to different land-use changes across Europe, Geoderma, 192, 189–201, https://doi.org/10.1016/j.geoderma.2012.08.003, 2013.

Poeplau, C., Jacobs, A., Don, A., Vos, C., Schneider, F., Wittnebel, M., Tieymeyer, B., Heidkamp, A., Prietz, R., and Flessa, H.: Stocks of organic carbon in German agricultural soils -Key results of the first comprehensive inventory, 183, 665–681, https://doi.org/10.1002/jpln.202000113, 2020.

Poeplau, C., Vos, C., and Don, A.: Soil organic carbon stocks are systematically overestimated by misuse of the parameters bulk density and rock fragment content, SOIL, 3, 61–66, https://doi.org/10.5194/soil-3-61-2017, 2017.

Porras, R. C., Hicks Pries, C. E., McFarlane, K. J., Hanson, P. J., and Torn, M. S.: Association with pedogenic iron and aluminum: effects on soil organic carbon storage and stability in four temperate forest soils, Biogeochemistry, 133, 333–345, https://doi.org/10.1007/s10533-017-0337-6, 2017.

Quesada, C. A., Paz, C., Oblitas Mendoza, E., Phillips, O. L., Saiz, G., and Lloyd, J.: Variations in soil chemical and physical properties explain basin-wide Amazon forest soil carbon concentrations, SOIL, 6, 53–88, https://doi.org/10.5194/soil-6-53-2020, 2020.

R Core Team: R: A Language and Environment for Statistical Computing, R Foundation for Statistical Computing, Vienna, 2019.

Rasmussen, C., Heckman, K., Wieder, W. R., Keiluweit, M., Lawrence, C. R., Berhe, A. A., Blankinship, J. C., Crow, S. E., Druhan, J. L., Hicks Pries, C. E., Marin-Spiotta, E., Plante, A. F., Schädel, C., Schimel, J. P., Sierra, C. A., Thompson, A., and Wagai, R.: Beyond clay: towards an improved set of variables for predicting soil organic matter content, Biogeochemistry, 137, 297–306, https://doi.org/10.1007/s10533-018-0424-3, 2018.

Scharlemann, J. P. W., Tanner, E. V. J., Hiederer, R., and Kapos, V.: Global soil carbon: understanding and managing the largest terrestrial carbon pool, Carbon Management, 5, 81–91, https://doi.org/10.4155/cmt.13.77, 2014.

Schwertmann: Differenzierung der Eisenoxide des Bodens durch Extraktion mit Ammoniumoxalat-Lösung, Journl of Plant Nutrition and Soil Science, 105, 194–202, https://doi.org/10.1002/jpln.3591050303, 1964.

Spohn, M. and Giani, L.: Total, hot water extractable, and oxidation-resistant carbon in sandy hydromorphic soils-analysis of a 220-year chronosequence, Plant Soil, 338, 183–192, https://doi.org/10.1007/s11104-010-0322-5, 2011.

Tokarski, D., Wiesmeier, M., Doležalová Weissmannová, H., Kalbitz, K., Scott Demyan, M., Kučerík, J., and Siewert, C.: Linking thermogravimetric data with soil organic carbon fractions, Geoderma, 362, 114124, https://doi.org/10.1016/j.geoderma.2019.114124, 2020.

Totsche, K. U., Amelung, W., Gerzabek, M. H., Guggenberger, G., Klumpp, E., Knief, C., Lehndorff, E., Mikutta, R., Peth, S., Prechtel, A., Ray, N., and Kögel-Knabner, I.: Microaggregates in soils, J. Plant Nutr. Soil Sci., 181, 104–136, https://doi.org/10.1002/jpln.201600451, 2018.

Vos, C., Don, A., Hobley, E. U., Prietz, R., Heidkamp, A., and Freibauer, A.: Factors controlling the variation in organic carbon stocks in agricultural soils of Germany, Eur J Soil Sci, 70, 550–564, https://doi.org/10.1111/ejss.12787, 2019.

Vos, C., Jaconi, A., Jacobs, A., and Don, A.: Hot regions of labile and stable soil organic carbon in Germany – Spatial variability and driving factors, SOIL, 4, 153–167, https://doi.org/10.5194/soil-4-153-2018, 2018.

https://doi.org/10.5194/soil-2021-81
Preprint. Discussion started: 27 August 2021

Wagner, W. H., Kremb-Wagner, F., Koziol, M., and Negendank, J. F. W. (Eds.): Trier und Umgebung, Schweizerbart Science Publishers, Stuttgart, Germany, 2011.

Wander, M.: Soil Organic Matter Fractions and Their Relevance to Soil Function, in: Soil Organic Matter in Sustainable Agriculture, edited by: Magdoff, F. and Weil, R., CRC Press, https://doi.org/10.1201/9780203496374.ch3, 2004.

Wardle, D. A.: A comparative assessment of factors which influence microbial biomass carbon and nitrogen levels in soil, Biological reviews, 67, 321–358, https://doi.org/10.1111/j.1469-185X.1992.tb00728.x, 1992.

Weigel, A., Eustice, T., van Antwerpen, R., Naidoo, G., and Schulz, E.: Soil Organic Carbon (SOC) changes indicated by Hot Water Extractable Carbon (HWEC), 84, 210–222, 2011.

Weigel, A., Kubat, J., Körschens, M., Powlson, D. S., and Mercik, S.: Determination of the decomposable part of soil organic matter in arable soils∗, Archives of Agronomy and Soil Science, 43, 123–143, https://doi.org/10.1080/03650349809366031, 1998.

Wiesmeier, M., Urbanski, L., Hobley, E., Lang, B., Lützow, M. von, Marin-Spiotta, E., van Wesemael, B., Rabot, E., Ließ, M., Garcia-Franco, N., Wollschläger, U., Vogel, H.-J., and Kögel-Knabner, I.: Soil organic carbon storage as a key function of soils - A review of drivers and indicators at various scales, Geoderma, 333, 149–162, https://doi.org/10.1016/j.geoderma.2018.07.026, 2019.

Wiesmeier, M., Barthold, F., Spörlein, P., Geuß, U., Hangen, E., Reischl, A., Schilling, B., Angst, G., Lützow, M. von, and Kögel-Knabner, I.: Estimation of total organic carbon storage and its driving factors in soils of Bavaria (southeast Germany), Geoderma Regional, 1, 67–78, https://doi.org/10.1016/j.geodrs.2014.09.001, 2014.

Wiesmeier, M., Hübner, R., Barthold, F., Spörlein, P., Geuß, U., Hangen, E., Reischl, A., Schilling, B., Lützow, M. von, and Kögel-Knabner, I.: Amount, distribution and driving factors of soil organic carbon and nitrogen in cropland and grassland soils of southeast Germany (Bavaria), Agriculture, Ecosystems & Environment, 176, 39–52, https://doi.org/10.1016/j.agee.2013.05.012, 2013.