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Regional spatial and vertical patterns of SOC stocks in a low mountain landscape in Germany

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ABSTRACT

Despite growing attention on soil organic carbon (SOC) stocks and dynamics, uncertainties persist in our understanding of their regulating factors, especially in the subsoil. Here, we examined regional patterns of SOC stocks and their relation to land use and other potential predictors, including average soil temperature, average soil moisture, and topography. To this end, we took 96 soil cores in the Fichtelgebirge mountains, Germany, including three different land use types (cropland, coniferous forest, and meadow) up to a depth of one meter, and sliced them into 10 cm increments.

The influence of land use was evident down to one meter but not across all soil depth increments. Coniferous forests exhibited the highest SOC stocks both in the topsoil (including the organic layer) and in total. On average, over 20 % of SOC was stored below 30 cm in all land use types, however with a high variability. Land use was the relatively most important factor explaining SOC stock patterns in the top 20 cm of soil. In the subsoil, climatic factors and topography became more relevant to explain the SOC stocks. Soil temperature was positively associated with SOC stocks in the topsoil, but this relationship reversed and became negative in deeper soil increments. A similar but less-pronounced trend with depth was observed for soil moisture. The declining relative importance of all predictors with depth underscores the need for high-resolution, depth-resolved field measurements to disentangle and quantify interactions among SOC stock predictors, particularly in the subsoil.

1. Introduction

Soil organic carbon (SOC) plays an important role in the carbon cycle, as it is the biggest terrestrial carbon reservoir (Jobbágy and Jackson, 2000). Safeguarding this crucial carbon pool is essential for mitigating climate change, as strategic management of SOC has emerged as a potential approach for sequestering atmospheric CO_2 (Lal, 2004; Paustian et al., 2019), while simultaneously preserving soil fertility and ensuring food security (Paustian et al., 2019; Poeplau et al., 2020). Therefore, increasing attention has been directed towards understanding stocks and dynamics of SOC, particularly SOC stabilization mechanisms and distribution across land use types and soil depths (Kögel-Knabner and Amelung, 2014; Wiesmeier et al., 2016).

Land use and management practices are among the key global drivers of SOC stock dynamics (Beillouin et al., 2022). Land use is associated with different vegetation types, which influence the potential carbon input into the soil via plant material (Reicosky et al., 1995). Both root depth and root biomass differ between perennial and annual plants. For example, Norway spruce can root down to 2.5 m while oats have 95% of the root biomass located in the upper 78 cm and maize in the upper 89 cm (Puhe, 1994; Canadell et al., 1996; Monti and Zatta, 2009). Also root traits further influence decomposition dynamics, with tree roots typically decomposing more slowly than herbaceous roots (Solly et al., 2014; Silver and Miya, 2001). Additionally, factors such as climate, topographical features (e.g., altitude) and soil properties (e.g., clay content) can also exert a significant influence on SOC stocks (Paltineanu et al., 2024; Poeplau et al., 2020). Topographic characteristics, such as the topographic wetness index (TWI), reflect potential zones of SOC accumulation and indicating areas of enhanced water retention driven by local relief (Sørensen et al., 2006). Together with climatic factors like precipitation and temperature, they influence soil

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moisture and temperature (Baumberger et al., 2025). These parameters regulate microbial activity and carbon decomposition, thereby affecting SOC stocks (Li et al., 2019; Coûteaux et al., 2001). Furthermore, plant growth and the associated carbon input to the soil are also regulated by climatic factors (Forstner et al., 2021). Moreover, soil properties — such as soil type and texture — also play a crucial role for SOC stock dynamics (Wiesmeier et al., 2015).

The relative impact of these drivers varies depending on spatial scale (Wiesmeier et al., 2019). For example, in Bavarian forests, pH, temperature, precipitation, parent material, slope, elevation, and clay content were identified as key determinants of SOC stocks in the topsoil (including the organic layer) while temperature, precipitation, and elevation were significant factors in the subsoil (Wiesmeier et al., 2013b). In agricultural soils of Bavaria, land-use history was identified as the dominant driver for SOC stocks in the topsoil, while soil type and topographic features were more relevant in the subsoil (Mayer et al., 2019). Kühnel et al. (2019) investigated SOC stock changes over the past 20 years in the top 10 cm of Bavarian grasslands and concluded that the main drivers were changing climatic conditions, land use management, and pedogenic-topographic factors. For agricultural soils in Germany, Vos et al. (2019) found that land use (and its history), clay content, and electrical conductivity (EC) were identified as the main drivers for topsoil SOC stocks, whereas the combination of parent material, relief, and EC were more influential in the subsoil. Thus, the impact of environmental factors on SOC stocks is strongly context-dependent—varying with spatial scale, geographic setting, and soil depth. In addition, the drivers can interact in complex ways. This highlights the need for more region-specific studies that incorporate multiple land-use types and vertical soil variability to better model SOC stocks and disentangle the combined effects of SOC stock driver as a basis for possible strategic SOC management (Muñoz-Rojas et al., 2012; Rial et al., 2017; Paustian et al., 2019).

Based on existing knowledge of spatial SOC stock patterns in Germany, croplands generally exhibit the lowest total SOC stocks, while grasslands have the highest, with forests representing intermediate values; however, variability between sites remains high (Poeplau et al., 2020; Wellbrock and Bolte, 2019). A similar pattern has also been reported for smaller regions within Germany, such as Bavaria (Wiesmeier et al., 2012). This study also shows that, in forest soils, the majority of SOC in the mineral soil is stored in the subsoil. Therefore, subsoil SOC stocks represent a particularly important carbon pool in forest ecosystems.

Many analyses are limited to the topsoil (Kühnel et al., 2019; Rial et al., 2017; Yigini and Panagos, 2016), or — as in the studies mentioned above — top- and subsoil are treated as two separate entities comparing both against each other. However, soils are vertically heterogeneous, with processes that vary in importance with soil depth, even within individual horizons. Also, some papers use a Pedotransfer function (PTF) for predicting bulk density instead of measuring at multiple depth to calculate SOC stocks, which can lead to high over- or underestimation, especially in the subsoil, where the stone content can be unpredictable (Rumpel and Kögel-Knabner, 2011; Bretas et al., 2025). Higher stone content leads to lower SOC stocks per unit volume, as the proportion of fine earth is reduced. Accurate determination of stone content is therefore essential to obtain reliable bulk density data and, consequently, precise SOC stock estimates (Poeplau et al., 2017). This need becomes particularly evident when considering the importance of subsoil carbon for the global soil carbon pool, as approximately 63–71% of the total soil carbon stored within the upper 100 cm of soil is located below 30 cm depth (Batjes, 2014). Therefore, it is important to investigate multiple depths precisely-especially of the subsoil.

Understanding the drivers of SOC stocks is essential for predicting ecosystem responses to environmental change. Identifying these drivers and possible predictors is also critical for accurately modeling the spatial distribution of SOC stocks across landscapes, thereby supporting the development of effective land management and carbon sequestration policies (Beillouin et al., 2022; Liu et al., 2015; Poeplau and Don, 2013). Such models are fundamental for forecasting future SOC stock dynamics and their responses to environmental change (Yigini and Panagos, 2016).

However, most research on SOC stock controlling factors has been conducted under laboratory conditions, with limited assessment of their relevance in natural environments (Rumpel and Kögel-Knabner, 2011). Because field conditions are inherently variable and lack the stability of controlled settings, advanced modeling approaches are required to disentangle and quantify the interactions among SOC stock predictors. Generalized linear mixed models (GLMM) allow flexible modeling of non-normally distributed response variables and estimate the effects of multiple explanatory variables while accounting for random effects such as spatial or sampling-related variability (Berridge and Crouchley, 2011). In contrast, Machine learning (ML) approaches are more complex, but particularly useful for assessing variable importance and exploring patterns in heterogeneous field data without requiring strong parametric assumptions (Ryo and Rillig, 2017).

Existing field studies, however, often focus exclusively on the topsoil (Rial et al., 2017), treat the subsoil as one entity (Angst et al., 2018), are limited to a single land use (Oppong Sarkodie et al., 2023), or rely on predicted rather than measured SOC values in the subsoil (Bretas et al., 2025). Therefore, additional field-based studies incorporating multiple land use types across the entire soil profile are urgently needed.

The aim of this study was to provide novel insights into spatial patterns of SOC stocks across various soil depths and their possible predictors on the regional scale — at the example of the Fichtelgebirge mountains (Bavaria, Germany). Since root depth and root biomass production differ substantially among meadows, cropland, and forests, and therefore carbon input (Jackson et al., 1996), we hypothesized that (i) land use has an effect on SOC stocks across all soil depths down to one meter, but (ii) its relative importance decreases with depth, where (iii) other factors such as topography and soil climatic conditions become more important. Extensive fieldwork was conducted to quantify SOC stocks across multiple depths (up to 1 m in 10 cm increments), land use types (meadow, cropland, and coniferous forest), and time points (96 sampling campaigns evenly distributed over one year). GLMMs were used to compare SOC stocks across depths and land-use categories. To study the joint effect of multiple predictors and complex interactions in more detail, we additionally used random forests in combination with explainable machine learning to gain insights into the relative importance of predictors. The trained model is further used for predicting the spatial and vertical patterns of SOC stocks within the landscape.

2. Methods

2.1. Study area and sampling

To determine SOC stocks, soil cores were taken in the Fichtelgebirge mountains, northeast Bavaria, Germany, in a 20 × 20 km square area around the “Großer Waldstein” (877 m a.s.l.). The study area is located in the temperate climate zone with an annual mean temperature of 6.5 °C and annual precipitation sum between 800 and 1000 mm (Bayerisches Landesamt für Umwelt, Germany, 2018a). The parent material is mainly weathered granite, weathered greywacke and partly bedrock dominated by amphibolite, and phyllite (Bayerisches Landesamt für Umwelt, Germany, 2018b; Rösch and Hahne, 2024). “Großer Waldstein” is part of the low mountain range “Fichtelgebirge” that extends diagonally from south-west to north-east through the study area and is predominantly covered by coniferous forest. The surrounding landscape is rural, characterized by agricultural land (cropland and grassland), interspersed with small forest patches and small towns and villages. Numerous rivers and streams flow through the area.

The area contains multiple land use types that are nearly evenly represented in terms of spatial coverage. They are characterized by similar parent material that results in similar soil types and textures. Yet, the study area exhibits climatic gradients due to its low-mountain terrain. These conditions allow us to exclude soil type and texture as potential SOC stock predictors and to focus instead on factors such as soil temperature and soil moisture.

The field campaign was conducted between December 2021 and December 2022. We sampled 32 plots per land use type (i.e. forest, meadow, cropland). As a sampling approach and to ensure randomization, we divided our study area into 64 grid cells (Fig. A.1). At each sampling date, one cell for each land use type was randomly selected. The plot location was chosen depending on approachability and permission. We ensured that no cell was sampled more than once per land use type. With this sampling design, we aimed to capture the full range of environmental gradients within each land-use type. For example, forest sites were selectively chosen at lower elevations and on gentle slopes, even though forests dominated at high elevations and/or steep slopes. This was necessary to ensure comparability with the other land-use types. No land-use type had significantly different soil moisture, soil temperature or TWI values compared to the others. We restricted the sampling to terrestrial soils: Cambisols and Cambic Podzols with a loamy texture were sampled (FAO) because they dominate in the study area. Other soil types that occur sporadically (e.g., gleysols) were excluded. Forest samples were taken in Norway spruce (*Picea abies L.*) dominated coniferous forests with an organic layer thickness between 4–18 cm.

2.2. Bulk density and SOC stocks

On each plot two soil cores were taken with a soil column cylinder auger (Eijkelkamp, 100 × 8 cm sampling size) and a gasoline driven hammer (Cobra 148, Atlas Copco). Each core was sliced in 10 cm increments, respectively, directly in the field. For determination of bulk density, one core set was dried at 105 °C and subsequently sieved (2 mm). Stone content was determined to avoid overestimation of the bulk density, which was calculated according to Eq. (1):

$$BD_{soil}\ [\mathrm{g/cm^3}] = \frac{mass_{soil}\ [\mathrm{g}]}{volume_{sam}\ [\mathrm{cm^3}] - \frac{mass_{stone}\ [\mathrm{g}]}{density_{stone}\ [\mathrm{g/cm^3}]}} \tag{1}$$

Mass$_{soil}$ is the total mass of soil < 2 mm of the volume of a sample (volume$_{sam}$). Coarser fractions were classified either as organic material (e.g. roots) or stone content (mass$_{stone}$). For the density of the stone content an approximating value of 2.6 g/cm^3 was used (Don et al., 2007). The second set of soil samples was sieved to 2 mm at field moist conditions and subsamples were dried at 40 °C. Also, roots of each soil sample were manually extracted, and its dry mass (40 °C) was determined. For organic carbon and nitrogen quantification, the dried soil was milled with an oscillating mill (MM40 Retsch) and measured with an element analyzer (EA/TC-IRMS Nu Horizon, Hekatech/Nu Instruments). The SOC stocks were calculated for each 10 cm increment separately using the following equation, suggested by Poeplau et al. (2017):

$$SOC_{stock}\ [\mathrm{t\ ha^{-1}}] = \frac{SOC_{con}\ [\%] * mass_{soil}\ [\mathrm{g}]}{volume_{sam}\ [\mathrm{cm^3}]} * depth\ [\mathrm{cm}] \tag{2}$$

where SOC$_{con}$ is the SOC content, mass$_{soil}$ the weight of dried and sieved soil in a known volume (volume$_{sam}$) multiplied by its depth/increment thickness.

Sampling to a depth of one meter was sometimes not possible due to lower soil thickness above the parent material. Therefore, the average values of soil properties in the deeper increments are based on a lower number of replicates than those of the topsoil, as indicated in Table 1. For the total SOC stocks all available soil core increments were summed up. In cases where the auger could not reach one meter due to bedrock, the SOC stock for that depth increment was assumed to be zero because the parent material was weathered granite and greywacke, often covered by a stone rich solifluction base layer that typically contains negligible proportions of fine soil. Due to the loamy texture, there was no problem with soil loss from the auger during extraction.

2.3. Predictor data

We complemented the data set with potential explanatory variables for SOC stocks: We selected land use type, mean annual soil temperature, mean annual soil moisture, TWI, and soil depth as predictors. These predictors were chosen due to their process-related relevance based on literature (Wiesmeier et al., 2019) and spatial availability for the study area to enable spatial predictions of SOC stocks. All data sets were available at a resolution of 10 m × 10 m for the 400 km^2 study area. We derived land use from the German land use map (Geobasisdaten: Bayerische Vermessungsverwaltung, 2020c) and differentiated between arable land and grasslands based on the German soil inventory (nationwide evaluation system for agricultural soil) (Geobasisdaten: Bayerische Vermessungsverwaltung, 2020a). We calculated the TWI from the digital elevation model (Geobasisdaten: Bayerische Vermessungsverwaltung, 2020b). For the mean annual soil temperature and the mean annual soil moisture, we used the spatial data from Baumberger et al. (2024), where both variables were modeled for our study area at 10 m spatial and hourly temporal resolution for the year 2022. For the organic layer, soil temperature and moisture were derived from predictions based on an extended version of the same model. We calculated an annual average of soil temperature and soil moisture for each depth and assumed that the year 2022 provides representative spatial patterns. The predictor values were extracted from the spatial predictor data for each measurement site.

2.4. Generalized linear mixed model

To test the effect of land use with depth on SOC stocks we used a generalized linear mixed model (GLMM) with the glmmTMB function of the same-named package (McGillycuddy et al., 2025) using R Statistical Software v.4.2.2 (R. Core Team, 2021). Residual diagnostics were performed using the DHARMa package (Hartig, 2022) and no spatial correlation was found. The response variable, the SOC stock, was square-root transformed to reduce heteroskedasticity and skewness in the distribution of the residuals. The model included depth, land use type, and their interaction as fixed effects, while allowing for a non-linear relationship between depth depending on the land use type and SOC stocks by incorporating a quadratic term. The plot ID was included as a random intercept. The Tweedie distribution was selected for the error structure due to the characteristics of the SOC stock distribution, which includes continuous, positive values, and many very low values. Dispersion was allowed to vary as a function of depth and land use type to account for heteroskedasticity within the SOC stock data to improve model fit.

There was still a small under-dispersion within the first 60 cm, below 60 cm a small over-dispersion, but estimated significance levels should be conservative. To determine at which depths the effects of depth and land use on SOC stock are significantly different, we performed pairwise comparisons at various depths based on the GLMM. To this end, we used EMMs (estimated marginal means) of the emmeans package (Lenth and Piaskowski, 2025) that provide a robust method for estimating and comparing SOC stock while adjusting for the effects of other co-variates in the model. Figures were conducted with the ggplot2 packages (Wickham, 2016).

Table 1
Soil properties derived from soil core increments. In total, 32 soil cores were sampled for each land use type, respectively. The number of replicates varies with sampling depth, as reaching bedrock before 100 cm prevented sampling at lower depths, thereby reducing the number of replicates in deeper increments. The mean and standard deviation was calculated for bulk density, stone content, SOC content and SOC stocks per 10 cm increment for cropland (Crop), coniferous forest (For) and meadow (Mea).

Depth	Nr of replicates (n)			Bulk density [g/cm^3]			Stone content [Vol%]			SOC content [%]			SOC stock [t ha^{-1}]		
[cm]	Crop	For	Mea	Crop	For	Mea	Crop	For	Mea	Crop	For	Mea	Crop	For	Mea
Organic layer	–	32	–	–	0.22 ±0.15	–	–	–	–	–	33.47 ±9.80	–	–	55.8 ±37.2	–
0–10	32	32	32	1.01 ±0.20	0.66 ±0.18	0.82 ±0.12	11 ±6	9 ±8	2 ±3	2.48 ±0.65	4.77 ±1.81	4.90 ±1.69	22.1 ±6.3	24.8 ±10.8	38.3 ±10.7
10–20	32	32	32	1.11 ±0.19	0.88 ±0.20	1.07 ±0.13	12 ±6	17 ±13	11 ±8	2.34 ±0.43	2.48 ±1.26	2.87 ±0.99	22.4 ±3.9	16.8 ±6.5	27.1 ±8.8
20–30	32	31	32	1.17 ±0.22	0.99 ±0.23	1.22 ±0.26	15 ±8	18 ±11	14 ±10	1.68 ±0.56	1.66 ±0.88	1.43 ±0.66	16.9 ±6.7	11.5 ±6.7	14.6 ±6.9
30–40	32	30	32	1.20 ±0.26	1.08 ±0.24	1.33 ±0.28	18 ±12	17 ±11	17 ±12	0.79 ±0.42	1.2 ±0.77	0.79 ±0.73	7.9 ±4.6	9.6 ±7.8	8.4 ±7.8
40–50	31	29	32	1.32 ±0.25	1.21 ±0.23	1.43 ±0.25	18 ±13	22 ±14	18 ±12	0.54 ±0.31	0.92 ±0.78	0.62 ±0.69	5.2 ±3.2	7.0 ±6.4	7.2 ±8.9
50–60	29	28	32	1.43 ±0.22	1.31 ±0.25	1.44 ±0.27	17 ±14	22 ±14	18 ±13	0.41 ±0.29	0.64 ±0.54	0.35 ±0.28	4.0 ±3.0	4.8 ±5.8	4.1 ±3.9
60–70	27	24	32	1.46 ±0.24	1.35 ±0.29	1.58 ±0.25	17 ±13	23 ±15	17 ±15	0.31 ±0.27	0.44 ±0.29	0.28 ±0.18	2.7 ±2.2	3.0 ±3.5	3.3 ±2.3
70–80	26	21	32	1.44 ±0.24	1.38 ±0.29	1.55 ±0.22	16 ±12	22 ±14	17 ±14	0.26 ±0.25	0.33 ±0.32	0.26 ±0.3	1.8 ±1.5	2.1 ±2.9	2.9 ±3.6
80–90	24	17	30	1.48 ±0.29	1.45 ±0.36	1.63 ±0.39	21 ±15	14 ±21	17 ±15	0.20 ±0.17	0.38 ±0.37	0.19 ±0.09	1.6 ±2.1	1.0 ±2.2	1.6 ±1.1
90–100	20	7	25	1.41 ±0.27	1.33 ±0.33	1.69 ±0.26	13 ±14	9 ±15	13 ±14	0.14 ±0.07	0.23 ±0.13	0.16 ±0.09	0.7 ±1.0	0.2 ±0.8	1.2 ±1.4

2.5. Random forest model

To investigate the complex relationship between SOC stocks and its predictors: land use type, mean annual soil temperature, mean annual soil moisture, TWI, and increment depth, we trained a random forest model. Therefore we used the R Statistical Software v.4.4.1 (R. Core Team, 2021) and the ranger package (Wright and Ziegler, 2017) for spatial prediction and for analyzing relationships between predictors and SOC stocks, as random forests can capture non-linear relationships, are robust to multicollinearity, and provide measures of variable importance, making them well suited for exploring complex interactions in heterogeneous field data. To estimate model and spatial prediction accuracy, we accounted for spatial dependence during model evaluation to avoid spatial leakage and overly optimistic performance estimates. Specifically, we tested a spatially informed cross-validation approach (Milà et al., 2022; Linnenbrink et al., 2024), which constructs folds such that the distribution of distances between training and validation locations reflects the distance structure between the training data and the prediction area. Due to the relatively even spatial distribution of the reference data across the study area, this approach resulted in cross-validation splits that were effectively similar to random splitting. We therefore proceeded with a random partitioning strategy. We separated an independent test set prior to model training by randomly selecting six measurement sites per land-use type and including all soil depths. The remaining sites were used for model training. For hyperparameter tuning, we applied 10-fold random cross-validation. Thereby, iteratively one fold was held back for validation and used to find the model with the lowest root mean squared error (RMSE), while testing all combinations of the hyperparameters mtry (number of predictors in each split) and the minimum node size. We used a fixed number of 100 trees in the random forest. A final model was trained with the best hyperparameters mtry = 2 and minimum node size = 20. We applied the trained model on the test set to determine the prediction performance. As a performance measure, we calculated the RMSE and the coefficient of determination R^2. To make spatial predictions of SOC stocks within the study area, we applied the trained model to the spatial raster data of the five predictors land use type, mean annual soil temperature, mean annual soil moisture, TWI, and increment depth, arriving at 10 m resolution spatial predictions of SOC stocks for the entire 20 km × 20 km study area. Since we had several increment depths, we spatially predicted SOC stocks for each depth separately by including the respective increment depth. This allowed to make a prediction of SOC stocks for the study area in 10 cm increment down to a depth of 90 cm (90–100 cm soil depth was not predicted due to missing spatial rater data of mean annual soil temperature and mean annual soil moisture). To estimate the spatial reliability of the model predictions for each depth, we calculated the dissimilarity index for the predictors in each pixel on the basis of which we defined the area of applicability (Meyer and Pebesma, 2021). This excludes model predictions for conditions that differ from the training data, i.e the model was not trained for these conditions and predictions have to be considered highly uncertain.

2.6. Shapley additive explanation

We used Shapley additive explanation (SHAP), an interpretable machine learning method, to analyze the relationships learned by the random forest to model SOC stocks. SHAP values were computed and visualized in R Statistical Software v.4.4.1 (R. Core Team, 2021) using the TreeSHAP (Lundberg et al., 2020) and shapviz packages (Mayer, 2022). Shapley additive explanation describes the effect of the respective predictor values on the target variable (Lundberg and Lee, 2017), i.e. SOC stocks. SHAP values and SHAP importance was determined for all soil depths, but also separately for each depth by splitting the data according to soil depth. From this, we determined the effects of the predictors land use type, mean annual soil temperature, mean annual soil moisture and TWI on SOC stocks for each depth.

3. Results

3.1. Soil properties of the extracted soil cores

Soil samples were collected down to a depth of 1 meter; however, in some cases, the auger could not reach the full 100 cm due to shallow soil profiles or the presence of large stones. This was particularly the case in the coniferous forest (Table 1).

Soil bulk density generally increased with depth across all land use types. Meadow soil was on average marginally denser compared to cropland soils and soil of coniferous forests was slightly less dense than cropland soil.

Stone content varied between 9–23 Vol% in agricultural soil (croplands and meadows), except for the first 10 cm of meadows, where on average only 2% of the volume were stones. In coniferous forests, the average stone content was, except for the first 10 cm and the last 20 cm, higher than in meadows and croplands and varied between 10%–25% on average. The standard deviation consistently exceeded 50% of the mean, sometimes even exceeding the mean (meadow 0–10 cm & 90–100 cm, forest 80–90 cm & 90–100 cm, cropland 90–100 cm).

SOC content exhibited a pronounced decrease with depth in coniferous forest and meadow soils, while remaining relatively consistent in the top 30 cm of cropland soil before declining. Generally, the highest SOC content was observed in coniferous forests, followed by meadows and croplands.

When considering SOC stocks per 10 cm depth increment, meadow soils exhibited the highest average SOC stocks in the upper 20 cm (excluding the organic layer), despite higher SOC concentrations in forest soils, due to their lower bulk density. At 20–30 cm depth, cropland showed the highest SOC stocks. Between 30 and 60 cm, coniferous forests had the highest SOC stocks per depth increment, whereas from 60 to 100 cm, meadow soils again exhibited the highest values.

3.2. Influence of land use on SOC stocks

The total SOC stock within one meter varied significantly across all land use types, with coniferous forest exhibiting the largest SOC stock with 137 ± 52 t ha^{-1} (organic layer included), followed by meadow 109 ± 32 t ha^{-1} and cropland 85 ± 23 t ha^{-1} (Fig. 1).

This pattern persisted even when considering only the topsoil (0–30 cm), where forest significantly maintained the highest stock. The subsoil SOC stocks of meadow, croplands, and coniferous forest showed a different trend. There were no significant differences between the land use types, where SOC stocks varied between 24–31 t ha^{-1}, on average.

Examining the distribution of total SOC stocks within one land use until one meter depth (Fig. 2) revealed that across all land use types, the highest SOC stock (> 72%) was concentrated near the surface (0–30 cm) with a notable decline in the SOC stock with increasing depth.

Coniferous forest soils stored on average 40% of their total SOC stock in the organic layer alone and 58% when including the first 10 cm. Approximately 80% of the total SOC stock in coniferous forests was concentrated within the organic layer and topsoil (0–30 cm).

In agricultural soil almost 75% (72% cropland and 74% meadows) of the total SOC stock was stored in the topsoil on average. SOC stocks in coniferous forest and meadow soils decreased almost exponentially with depth, whereas cropland soils exhibited a more uniform distribution within the top 30 cm. However, more than 20% of the total SOC stock was stored in the subsoil across all land use types.

A detailed look at the distribution of the SOC stock in the mineral soil per depth (Fig. 3) showed again, that the SOC stocks continually decreased with increasing soil depth across all land use types. This trend was most pronounced in the top 40 cm of soil, where the decline in SOC stocks was steepest and became more gradual with depth. Among the land use types, meadows exhibited the highest SOC stock values in the upper 20 cm of mineral soil, then coniferous forests had the highest SOC stocks per depth increment. Croplands consistently had the lowest or second lowest SOC stock values throughout the soil profile. It should be noted that there was a high variability in all land use types within the data, especially in the upper soil increments.

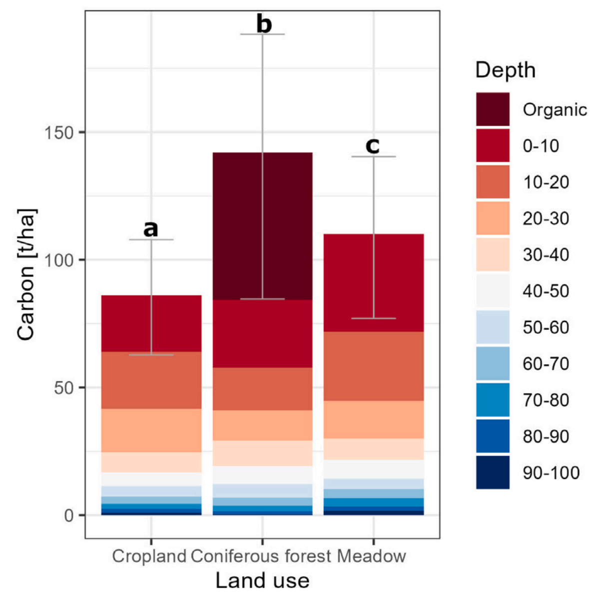

Fig. 1. Accumulated SOC stocks per land use. The mean stocks of each depth increment are accumulated for each land use, respectively. Bars that do not share a letter differ significantly from each other ($p < 0.05$). In case that bedrock was reached within 100 cm depth, SOC stocks of the respective depth increments were considered to be zero to calculate realistic SOC stocks in our study area (n=32).

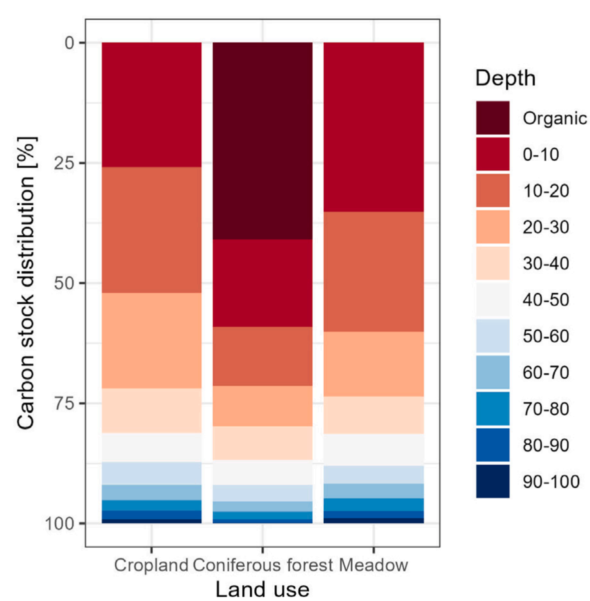

Fig. 2. Depth distribution of SOC stocks per land use type in percentage, expressed as the percentage of total SOC stock stored in each depth increment. In case that bedrock was reached within 100 cm depth, SOC stocks of the respective depth increments were considered to be zero to calculate realistic SOC stocks in our study area (n=32).

Significant differences were observed at various depths within one meter (Table 2). In the 0–10 cm increment, meadows contained significantly higher SOC stocks compared to both croplands and coniferous forests, with estimated mean differences of −14.57 t ha^{-1} (cropland–meadow) and −17.30 t ha^{-1} (forest–meadow). This meadow–forest difference persisted in the 10–20 cm increment and appeared again in 50–60 cm, but with coniferous forests exhibited higher SOC stocks than

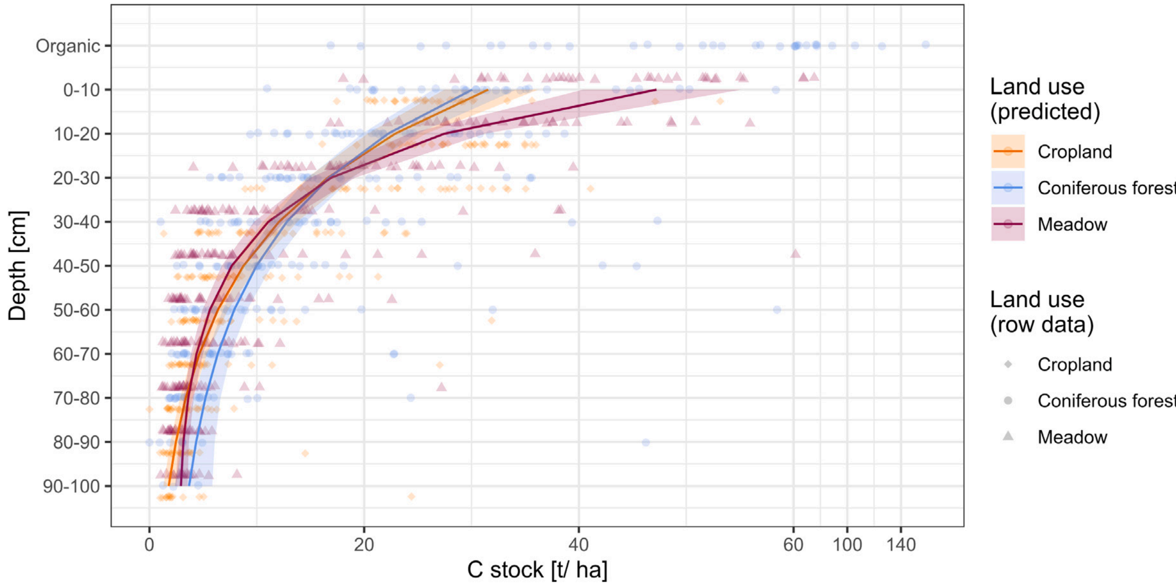

Fig. 3. Relationship between SOC stock (t ha^{-1}) and soil depth (cm) across different land use types (cropland, coniferous forest, meadow). The data points and predicted lines (GLMM model) with a confidence interval (95%) illustrate how SOC stocks decrease with depth for each land use type.

Table 2
Predicted differences between the SOC stocks of cropland, coniferous forest and meadow [t ha^{-1}]. The difference between the means (estimated marginal means) are based on the model (n=17–32).

Depth	Cropland-forest	Cropland-meadow	Forest-meadow
0–10	2.73	−14.57*	−17.30*
10–20	1.09	−4.63	−5.73*
20–30	0.15	−0.98	−1.13
30–40	−0.39	0.20	0.58
40–50	−0.67	0.42	1.09
50–60	−0.82	0.29	1.11*
60–70	−0.88	0.05	0.93
70–80	−0.90	−0.22	0.69
80–90	−0.90	−0.48	0.41
90–100	−0.88	−0.76*	0.12

* Significant differences are marked with an asterisk.

meadows. Between 20–50 cm and 60–90 cm, no significant differences among land uses were detected. Significantly lower SOC stocks in croplands compared to meadows appeared only in the deepest increment (90–100 cm), after the initial difference in the 0–10 cm increment. No significant differences in SOC stocks between cropland and coniferous forest soils were observed in any depth.

3.3. Influence of topography, land use, soil temperature and moisture on SOC stocks

SHAP values allow to determine whether specific land use types or feature values (e.g., low or high soil temperature) contribute positively or negatively to SOC stocks. Analysis of the SHAP importance of land use, mean soil temperature and moisture, and topographic wetness index (TWI) on SOC stocks revealed a decreasing influence of land use with soil depth. With this decreasing importance of the land use type, soil climatological factors (soil temperature and soil moisture) as well as topography (described as TWI) become more relevant for SOC stocks in the deeper soil increments. However, the SHAP importance of soil temperature, soil moisture and TWI varied across depths (Fig. 4b).

In the first 10 cm, meadows were associated with the highest, while croplands were associated with the lowest SOC stocks (Fig. 4 a). Coniferous forests, in contrast, were associated with SOC stocks that were slightly below the predicted mean values. Between 10–20 cm, forests and croplands reversed their relative impacts, with forest soils having the lowest SOC stocks compared to meadow and cropland. Meadows continued to have higher SOC stocks. Beyond this depth, the influence of land use gradually diminished, as indicated by the convergence of the point clouds near the center. Between 20–60 cm, meadow soils remained associated with slightly elevated SOC stocks, while cropland and forest soils generally showed lower values. An exception was the 20–30 cm increment, where cropland had SOC stocks above the mean. At greater depths (60–90 cm), the influence of land use became negligible, with no clear trends observable.

Soil temperature influenced SOC stocks differently across depth increments. In the organic layer, lower soil temperatures were associated with lower SOC stocks. In the topsoil, this trend was still present, but it reversed below 30 cm where low temperature values were coupled with higher SOC stocks. Across all depths, there was a positive trend with soil temperature and SOC stocks.

A similar profile pattern to that of soil temperature was observed for soil moisture; however, no clear trend was visible in the organic layer. Additionally, the positive effect of soil moisture in the topsoil was less pronounced. When comparing all depths, the negative trend in the subsoil was more dominant than the slight positive trend in the topsoil—opposite to the pattern observed for soil temperature.

Low TWI values were associated with both below- and above-average SOC stocks, indicating no consistent pattern. Only high TWI values showed a slight trend, with a negative influence on SOC stocks in the organic layer and upper 40 cm, followed by a minor positive influence at greater depths. Over all depths, no clear or consistent pattern was observed in relation to TWI.

When comparing all predictors based on their SHAP importance, soil temperature and TWI showed by far the highest relative importance in the organic layer. Land use types had the greatest relative influence in the top 20 cm of the soil profile, with their impact decreasing markedly with depth. Below 20 cm, SOC stocks were primarily influenced by soil climate and topographic parameters, which exhibited similar relative importance and a decreasing impact with depth.

For spatial predictions of SOC stocks across multiple soil depths (Fig. 5), the random forest model was used. Model performance evaluation revealed a RMSE of 7.61 t ha^{-1} and a R^2 showing the proportion of explained variance of 0.78.

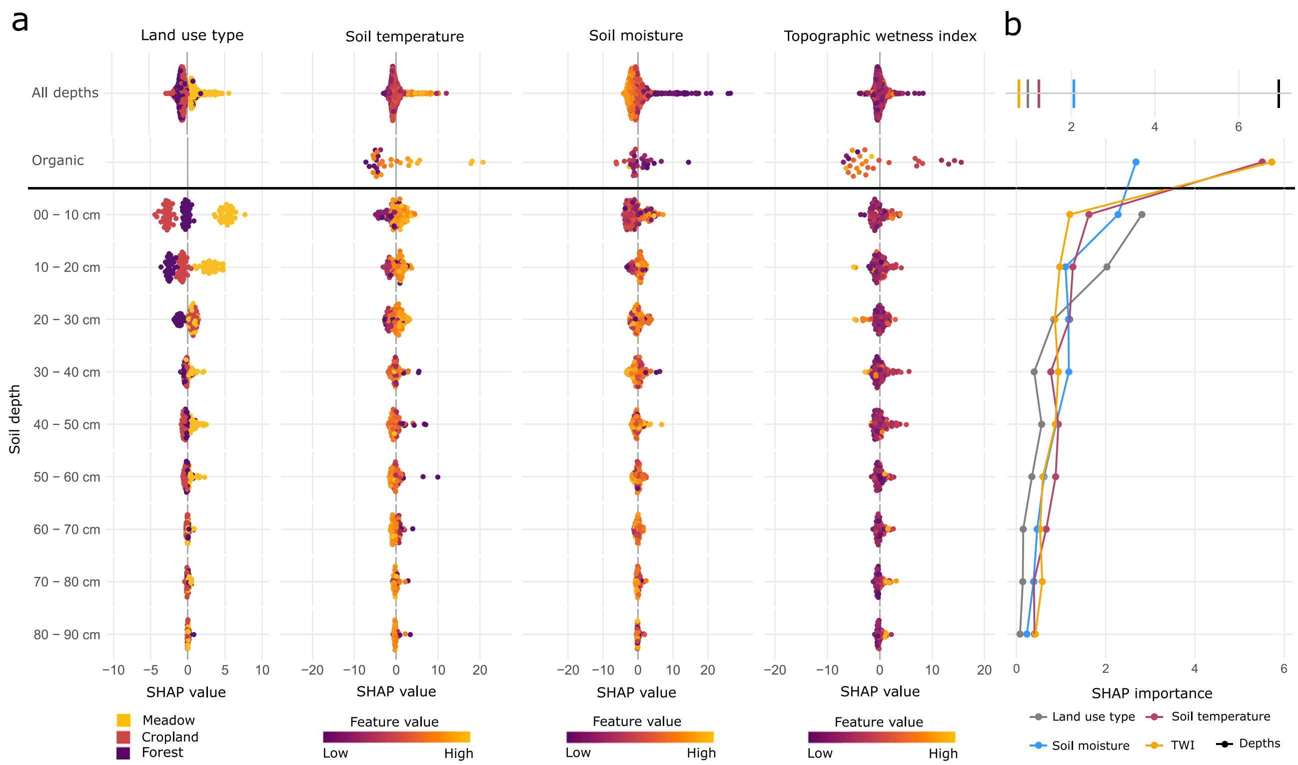

Fig. 4. **a** Shapley additive explanation (SHAP) values for the predictors across all depths (top row) and separated per depth. The position of a point on the x-axis determines the effect (positive or negative) of the predictor on the target variable SOC, whereby the color indicates whether the predictor value is high or low. In case of land use the color indicate the respective land use type. **b** SHAP importance of the predictors for all depths (top row) and separated per depth.

The highest SOC stocks per depth were predicted in the organic layer of the forest with values between 40 t ha^{-1} and 80 t ha^{-1}. The SOC stocks were comparatively low in the center of the study area along the mountain range, while the highest SOC stocks were predicted in the coniferous forests located in the lower plain. In mineral soils, SOC stocks of individual depth increments were predicted between 0 t ha^{-1} and 40 t ha^{-1}, decreasing with depth. At a depth of 0–10 cm, meadows exhibited markedly elevated SOC stocks compared to the other land use types. At soil depths of 10–20 cm and 20–30 cm, the structures of the forest areas with lower SOC stocks than in meadows and cropland were clearly visible. Below a soil depth of 30 cm, only small variations were evident within the study area but the structure of the mountain range, which extends diagonally from the south-west to the north-east through the study area, was still reflected in the SOC stock patterns across all depth increments. Along the mountain range, large areas were outside the area of applicability as the bedrock was close to the surface and the soil cores could not always be taken down to a depth of 1 m and thus there were less training data available for the deeper increments here (Table 1). Predictions were made for the whole study area, including semi-terrestrial and stagnic soils even though data were collected exclusively on terrestrial soils. These areas were predominantly outside the area of applicability, as the moisture conditions differed from those in the training data. Consequently, the area of applicability limits the SOC stock predictions to the reliable ones — including areas and depths for which sufficient and representative training data were available (Fig. 5).

4. Discussion

4.1. Land use effect on total SOC stocks

SOC stocks declined with increasing depth, yet the subsoil (30–100 cm) still contained more than 23 t ha^{-1}, corresponding to about 20% of the total SOC stored down to 1 m (Fig. 2). In agricultural soils (including croplands and meadows), the relative contribution of subsoil SOC to the total SOC stock was slightly higher (26%) than in forests, but still markedly lower than the 36% reported for Bavaria by Mayer et al. (2019). While their mean topsoil SOC stock (71.7 t ha^{-1}) was comparable to our estimate (70.7 t ha^{-1}), their mean subsoil SOC stock was substantially greater (41.5 t ha^{-1} versus 26.3 t ha^{-1} for meadow and cropland soils in our study (Table 1). Mayer et al. (2019) identified soil type as a dominant control on SOC stocks, showing that agriculturally managed Cambisols store less SOC in both topsoil and subsoil than other soil types such as Gleysols or Colluvisols. In contrast, major landform was highlighted as a key predictor of SOC stocks, with higher values on plains (< 2°) and gently sloping terrain (2–6°) compared to steeper slopes. Notably, 98% of our sampled plots were located on slopes < 6°. Taken together, these findings suggest that contrasting abiotic conditions explain our results: lower subsoil SOC stocks than those previously reported are likely influenced by the predominance of Cambisols in our study area, whereas topsoil SOC stocks remain close to the regional mean due to the dominance of gently sloping landforms, less dependent of soil type.

Croplands had the lowest SOC stock within one meter (or down to bedrock) compared to forest and meadow soils (Fig. 1). This finding is consistent with the representative inventory of total SOC stocks in Bavaria by Wiesmeier et al. (2012) as well as with the national inventory of agricultural soils (Vos et al., 2019). The German inventory study concluded that topsoil SOC stocks are primarily influenced by land use, whereas subsoil SOC stocks are shaped by other factors such as parent material and relief. Our finding supports the hypothesis that the impact of the intensity of agricultural use on SOC stocks is mainly restricted to the topsoil.

In a study focusing on the state Bavaria including the Fichtelgebirge mountains, Wiesmeier et al. (2013a) concluded that differences in SOC stocks between meadows and croplands were primarily driven by soil moisture–induced SOC stabilization in the subsoil. In contrast, our results indicate that the larger total SOC stock observed in meadows

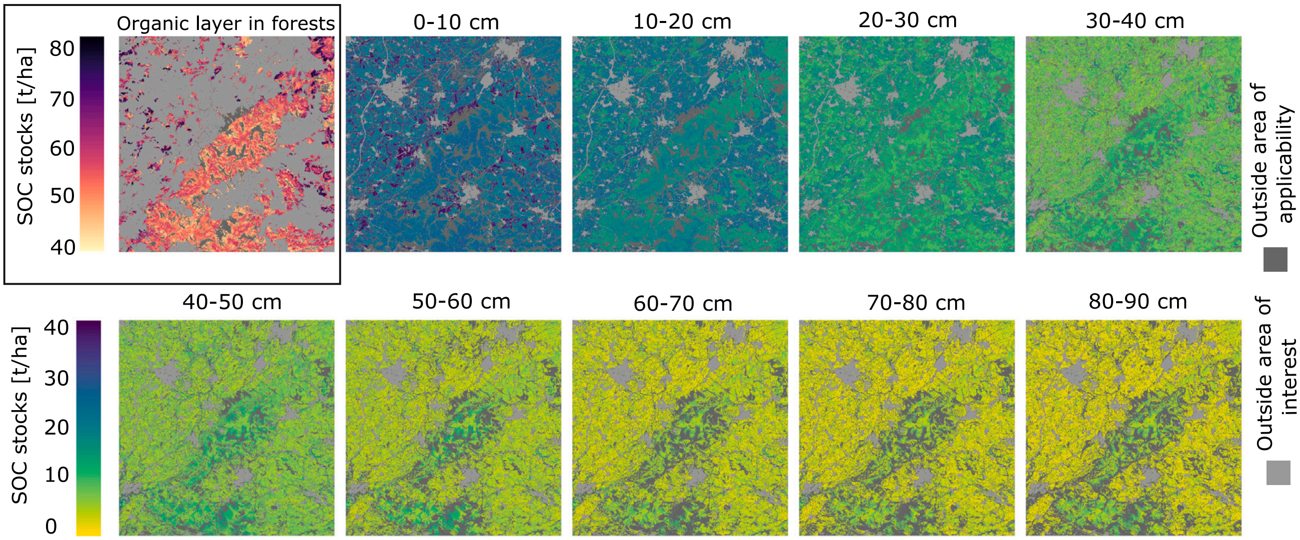

Fig. 5. Predicted SOC stocks for multiple soil increments in the 20 km × 20 km large study area in the Fichtelgebirge mountains, Germany. The top left panel shows the SOC stocks of the organic layer, which was only present in forests. The remaining panels show SOC stocks in the mineral soil in 10 cm segments down to a soil depth of 90 cm.

is mainly attributable to higher SOC stocks in the topsoil. A possible explanation for this discrepancy lies in the extend of the study area: Wiesmeier et al. (2013a) considered sites across the entire state of Bavaria, covering a wide variety of climatic conditions and parent materials, whereas our study was conducted within a comparatively small region with limited climatic variation and relatively uniform parent material. Also, soils with permanently high soil moisture, such as fluvisols or gleysols, were excluded from our study. However, the national inventory by Vos et al. (2019), which covers an even wider range of climatic conditions and parent materials across all soil groups, supports our findings. Again, the spatial scale may provide an explanation, as soil moisture–induced SOC stabilization in the subsoil could play a particularly important role in Bavaria, with its numerous mountain ranges (Wiesmeier et al., 2013a), but may be less relevant at the national scale across Germany. Also, it is important to note that soil properties and environmental conditions influence the choice of land use type (Poeplau et al., 2020), as for example fertile soils with favorable climatic conditions are preferentially used as croplands. This might be especially evident at a regional scale, but possibly less at state or national scale. Altogether, this highlights the importance of investigating SOC stock predictors also on a regional scales in order to disentangle the complex interactions among multiple influencing factors.

While the representative inventory of total SOC stocks in Bavaria (Wiesmeier et al., 2012) showed meadows to have higher SOC stocks than forests, our study revealed that coniferous forests had the highest SOC stocks, despite shallower soil profiles (< 100 cm) compared to other land use types (Table 1). Total SOC stock in coniferous forest was 136.6 t ha^{-1} and 80% was stored above 30 cm. This is above the median for Bavarian forests, but still aligns with the ranges reported by Wiesmeier et al. (2012) and the Bavarian Forest Soil Inventory (Schubert, 2010). Total SOC stocks in Bavarian forests were strongly influenced by climate factors (temperature and precipitation) (Wiesmeier et al., 2013b). Thus, the high SOC stocks in the coniferous forests of the Fichtelgebirge low mountain range may be attributed to the region's cold and humid climate, which promotes organic carbon accumulation in Bavarian forests (Wiesmeier et al., 2013b). This supports previous findings, that SOC storage is probably not solely determined by land use, a point that will be elaborated in the Section 4.3 section.

4.2. Land use effect by depth

Land use had a significant effect on total SOC stocks within the upper one meter. These findings were supported by previous studies (Vos et al., 2019; Poeplau and Don, 2013; Mueller and Koegel-Knabner, 2009), but, to our knowledge, it is the first study showing that the influence of land use on SOC stocks is not consistent across all depths at a regional scale (Table 2). In the upper 10 cm, significant differences were observed between cropland and meadows, and between coniferous forest and meadow, while no significant differences were found between cropland and forest despite the contrasting properties of these land use types. The rather low SOC stocks in croplands in the first 10 cm likely result, among others, from regular plowing and mixing of plant residues within the first 30 cm, thereby preventing SOC accumulation at the soil surface (Fig. 1). In coniferous forests, SOC stocks were comparable to those of croplands despite higher SOC content. This can be mainly attributed to the low bulk density of forest soils in the top 10 cm (Table 1).

Meadows are consistently observed to store more SOC than croplands in total, as also documented by Hassink (1997), Paltineanu et al. (2024), Wiesmeier et al. (2012, 2013a). This may result from a higher proportion of root-derived carbon in meadows, as suggested by Jacobs et al. (2020), rather than differences in carbon input quantity. However, our study indicates that this difference arises mainly from higher SOC stocks in the topsoil, particularly the first 10 cm (Fig. 3). Despite different root depth and root abundance between permanent vegetation and annual crops (Lasisi et al., 2018; Monti and Zatta, 2009), no significant difference in SOC stocks was observed between meadows and cropland below this depth.

Other studies have also found that the effect of land use on SOC stocks in German agricultural soils is confined to the topsoil (Vos et al., 2019). However, our detailed analysis showed significant differences between meadows and cropland in the 0–10 cm and 90–100 cm increment, but the difference in the deepest increment was rather small with 0.76 t ha^{-1} on average compared to the 14.57 t ha^{-1} in the 0–10 cm increment (Table 2). Thus, the effect is mainly restricted to the surface. This is particularly relevant, as the soil surface is highly vulnerable to changing climatic conditions, one of the main predictors of SOC stocks in Bavarian meadows (Kühnel et al., 2019).

Despite carbon losses due to biomass removal by mowing or grazing, meadows exhibited significantly higher SOC stocks in the first

20 cm than coniferous forests (Table 2). This may be explained by fertilization of the meadows in the study area, which can enhance SOC stocks (Poeplau et al., 2018). Additionally, a substantial proportion of SOC in the coniferous forests in our study — on average 41% — is stored in the organic layer above the mineral soil. Coniferous forests are characterized by low pH and slow SOC turnover (Amelung et al., 2018), which explains the observed accumulation of SOC as organic layer (on average 9 cm) above the mineral soil. Still, in mineral soil, the highest SOC content among all land use types and depths occurred in the top 10 cm in forest soils. Yet, the bulk density was about 23% lower in the topsoil compared to meadow soils. SOC content consistently decreased with depth while bulk density increased, except in the 90–100 cm increment (Table 1). This resulted in significantly higher subsoil SOC stocks in forests compared to meadows (50–60 cm). This is likely attributable to deeper tree root systems contributing to organic carbon input directly into the subsoil (Heinze et al., 2018; Angst et al., 2018). Indeed, larger amounts of roots were recorded in soil samples of forests than of meadows and croplands (root dry biomass in 30–100 cm: cropland 35 g ± 44 g, coniferous forest 546 g ± 553 g, meadow 28 g ± 30 g, data not shown). Below 40 cm, the number of coniferous forest samples declined because many forest soils were shallower than 100 cm (only 20 of 32 profiles reached full depth), whereas all meadow soils exceeded at least 80 cm depth (Table 1). This reduced sampling depth in coniferous forests resulted in lower observed SOC stocks in the subsoil and may explain why SOC stocks below 60 cm were not significantly higher in coniferous forests compared to meadows.

Statistically significant differences in SOC stocks per 10 cm increment between land use types were observed only in the 0–20 cm, 50–60 cm, and 90–100 cm increments, with no detectable variation between 20–40 cm and 50–90 cm. Although an aggregated comparison of topsoil versus subsoil suggested a land use effect limited to the topsoil, our detailed analysis revealed significant differences among land uses within specific subsoil depths. This highlights the importance of conducting comprehensive, depth-resolved soil studies to accurately assess SOC stocks and dynamics across different land use types—particularly when comparing agricultural soils with coniferous forest soils.

As outlined above, significant differences in SOC stocks were observed down to 100 cm, but not consistently across all depth increments. Consequently, we must reject our initial hypothesis (i) that land use has a detectable effect on SOC stocks at every measured depth increment.

4.3. Effect of topography, soil climate and land use on SOC stocks

While land use had a significant impact on SOC stocks, other factors such as soil climate, topography, soil texture, and bedrock material also play crucial roles (Mayer et al., 2019; Vos et al., 2019; Wiesmeier et al., 2019; Poeplau et al., 2020). In our study, conducted within a relatively small area of 40 km^2, the bedrock was predominantly granite, and soil texture varied only from sandy loam to loamy sand (according to German Soil classification (Sponagel et al., 2005)). These relatively uniform conditions allowed us to minimize the influence of factors such as parent material, enabling a more detailed assessment of the effects of land use, topography, soil temperature, and soil moisture on SOC stocks across different depths.

Land use had the highest SHAP importance within the top 20 cm, whereas abiotic factors had higher SHAP importance below this depth (Fig. 4). This could indicate that topsoil SOC stock dynamics are mainly driven by different carbon inputs, as regulated by vegetation type, whereas carbon input patterns are less important in the subsoil - a conclusion consistent with (Vos et al., 2019). In addition, tillage usually affects the upper 30 cm of cropland soils, which alters the SOC stocks (Alcántara et al., 2016) due to SOC relocation and reduced bulk density. The higher importance of land use in the topsoil was also reported in other studies (Mayer et al., 2019; Vos et al., 2019), but our data showed the decreasing importance with depth.

Across all depths, SHAP values indicated higher SOC stocks in meadows and lower SOC stocks in coniferous forests and croplands, despite the higher total SOC stocks observed in coniferous forests. This discrepancy arose because the organic layer, which contributes substantially to SOC stocks in forests, was separated in the prediction. Cropland was associated with the lowest SOC stocks in the first 10 cm, but with higher SOC stocks in 20–30 cm than average. This may resulted from SOC relocation to deeper topsoil increments by plowing. The higher meadow SOC stocks in the topsoil are probably a result of fertilization and the root biomass, as discussed above. Between 30–60 cm, meadow soils remained associated with higher SOC stocks, while forest and cropland soils were linked to lower SOC stocks, despite the significantly higher stocks in coniferous forests compared to meadows. Bioturbation plays a key role in the translocation of SOC into deeper soil increments (Rumpel and Kögel-Knabner, 2011). However, bioturbation is typically limited in coniferous forest soils due to acidic conditions, resulting in lower biological mixing compared to meadows (Taylor et al., 2019). In croplands, tillage can further disrupt bioturbation processes (Torppa and Taylor, 2022), potentially limiting the downward transport of organic matter and contributing to lower SOC stocks in deeper soil increments.

Climate factors, such as soil temperature and moisture regulate SOC stocks by influencing microbial activity and carbon decomposition (Li et al., 2019; Coûteaux et al., 2001) and also plant growth and therewith carbon supply to the soil (Forstner et al., 2021). Additionally, water can also lead to translocation of SOC to deeper soil increments (Lorenz and Lal, 2005). Our results generally indicated a positive association between SOC stocks and soil temperature, particularly in the topsoil, including the organic layer. However, with increasing depth, this trend reversed. Increased temperature can stimulate biomass production (Forstner et al., 2021), thereby enhancing SOC inputs; however, it can also accelerate decomposition rates (Meyer et al., 2018). It is plausible that the amount of carbon input plays a greater role in maintaining SOC stocks in the topsoil, whereas the faster decomposition rate is comparatively more important in the subsoil. Thus, soil temperature has a different influence depending on depth, but for the total SOC stocks higher temperatures were associated with higher SOC stocks.

Soil moisture showed the opposite trend for the total SOC stocks, but had a similar profile pattern: low soil moisture was associated with low SOC stocks in the topsoil, but this relationship shifted at greater depths till 40 cm. Below this depth, no clear trend was visible. Low soil moisture and droughts can reduce biomass production resulting in lower carbon inputs (Deng et al., 2021), whereas limited water availability inhibits carbon decomposition (Xiao et al., 2023). In our study area, drought-induced inhibition of SOC decomposition likely had a greater impact in the subsoil, whereas reductions in biomass production under drought were more relevant for topsoil SOC stocks. The higher total SOC stocks observed under lower soil moisture suggest that decomposition inhibition was the dominant influence. Consequently, total SOC stocks appeared to be negatively influenced by soil moisture, although this effect was also depth-dependent.

Both soil climate factors exhibited a similar but decreasing SHAP importance with depth, except for the organic layer. Here, temperature and TWI had by far the highest importance. The importance of climate factors was also confirmed in Wiesmeier et al. (2013b) and Mayer et al. (2019) for Bavarian forest, meadow and croplands.

The topographic wetness index highlights areas where water but also plant material accumulates due to the topographic position. In the Fichtelgebirge mountains, no clear trend was observed despite a visible SHAP importance in every depth. There would be probably a clear trend if semi-terrestrial and stagnic soils were included as both Wiesmeier et al. (2019) and Mayer et al. (2019) found a positive correlation between TWI and total SOC stock in Bavarian land use systems.

In general, the importance of almost each predictor decreased with depth, paralleling a reduction in SOC stock differences among land-use types. Consequently, differences in subsoil SOC stocks may become more pronounced at larger spatial scales, such as state or national levels, where the range of abiotic predictors is broader. Nevertheless, substantial uncertainty in subsoil SOC stock predictors was also reported in a national-scale study by Mayer et al. (2019), underscoring the need for more comprehensive, depth-resolved datasets to develop effective strategies for enhancing subsoil carbon sequestration and preventing SOC losses.

The chosen predictors not only had direct effects but also interact with one another. Land use indirectly affects the soil climate parameters by altering soil temperature and moisture through plant interactions. For instance, plant shading can reduce soil temperature, while plant water uptake influences soil moisture availability. Conversely, land use type is also chosen by soil properties e.g. topography and climate (Poeplau et al., 2020) and higher elevation or the inclination of a slope can lead to different soil climates. In our study area, spatial land use patterns were driven by climate and topography: shallow, rocky and colder soils were predominantly forested and wetter soils were primary used for meadows (Baumberger et al., 2024). With ongoing climate change and the increasing frequency of summer droughts, wetter soils that are currently used as meadows may become more attractive for conversion to cropland, which — as shown in this study — stores less carbon in the subsoil.

Despite — and partly because of — the interdependence among predictors, it is essential to investigate them jointly to obtain a comprehensive understanding of SOC dynamics. For example, climatic conditions showed relatively low importance for SOC stocks in agricultural soils across Bavaria (Vos et al., 2019), whereas they were identified as major predictors in Bavarian forest soils (Wiesmeier et al., 2013b). This contrast underscores the need to consider both, all land use types and broader environmental factors, across the full soil profile (to at least one meter depth). In our study the relative importance of land use decreased with depth(ii) and the abiotic factors (TWI, soil temperature and soil moisture) become more important (iii). Such depth-resolved and integrative analyses are crucial for refining carbon models and improving predictions of SOC stocks under changing environmental conditions (Dubeux et al., 2024; Todd-Brown et al., 2013).

5. Conclusion

Our study demonstrated that land use influenced SOC stocks within a depth of 100 cm, but not consistently. This effect was detectable only through high-resolution sampling in 10 cm increments, whereas aggregated comparisons of topsoil versus subsoil could have masked these differences. Most SOC was stored in the topsoil, where it is primarily influenced by land use, whereas abiotic controls (TWI, soil temperature, and soil moisture) exert a stronger influence on SOC stocks in the larger soil volume (20–100 cm). Climate change is expected to modify soil temperature and moisture regimes, which may lead to changes in SOC dynamics that are not yet well understood. By examining SOC stock patterns in a region with relatively uniform soil type and texture, we highlighted the value of depth-resolved analysis for disentangling the effects of land use and environmental conditions.

CRediT authorship contribution statement

Bettina Haas: Writing – original draft, Visualization, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Maiken Baumberger:** Writing – review & editing, Visualization, Software, Investigation, Formal analysis, Data curation. **Mona Müller:** Writing – review & editing, Investigation. **Julian Schweers:** Writing – review & editing, Investigation. **Lisa Hülsmann:** Writing – review & editing, Supervision, Methodology. **Eva Lehndorff:** Writing – review & editing, Resources. **Hanna Meyer:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization. **Nele Meyer:** Writing – review & editing, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work Bettina Haas used ChatGPT (OpenAI) to support language editing and to improve clarity and readability. After using this tool, Bettina Haas reviewed and edited the content as needed and takes full responsibility for the content of the published article.

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Declaration of competing interest

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

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Appendix

See Fig. A.1.

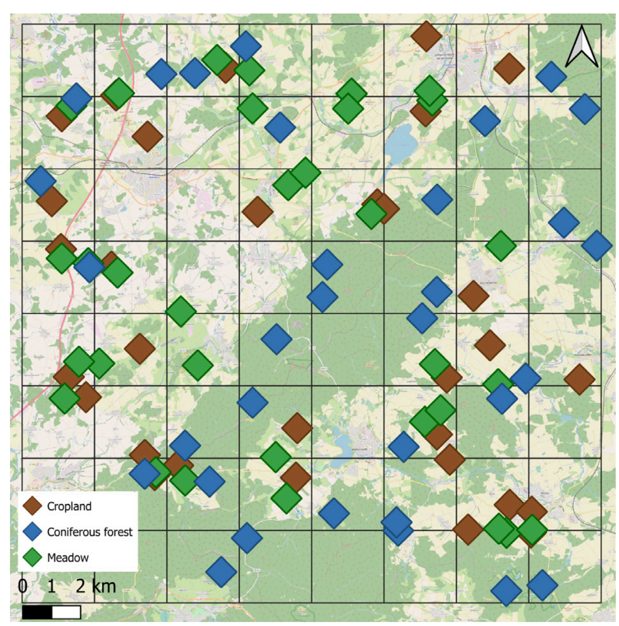

Fig. A.1. Study area map (OpenStreetMap, EPSG:3857) with an 8 × 8 grid used for plot selection (coordinates: 11.72° E–11.99° E, 50.05° N–50.24° N). Blue squares indicate coniferous forest plots, brown squares cropland, and green squares meadow sites.

Data availability

Data will be made available on request.

References

Alcántara, V., Don, A., Well, R., Nieder, R., 2016. Deep ploughing increases agricultural soil organic matter stocks. Global Change Biol. 22 (8), 2939–2956. http://dx.doi.org/10.1111/gcb.13289, URL: https://onlinelibrary.wiley.com/doi/10.1111/gcb.13289.

Amelung, W., Blume, H.P., Fleige, H., Horn, R., Kandeler, E., Kögel-Knabner, I., Kretzschmar, R., Stahr, K., Wilke, B.M., 2018. Scheffer/Schachtschabel Lehrbuch der Bodenkunde. Springer Berlin Heidelberg, Berlin, Heidelberg, http://dx.doi.org/10.1007/978-3-662-55871-3, URL: http://link.springer.com/10.1007/978-3-662-55871-3.

Angst, G., Messinger, J., Greiner, M., Häusler, W., Hertel, D., Kirfel, K., Kögel-Knabner, I., Leuschner, C., Rethemeyer, J., Mueller, C.W., 2018. Soil organic carbon stocks in topsoil and subsoil controlled by parent material, carbon input in the rhizosphere, and microbial-derived compounds. Soil Biol. Biochem. 122, 19–30. http://dx.doi.org/10.1016/j.soilbio.2018.03.026, URL: https://linkinghub.elsevier.com/retrieve/pii/S0038071718301093.

Batjes, N.H., 2014. Total carbon and nitrogen in the soils of the world. Eur. J. Soil Sci. 65 (1), 10–21. http://dx.doi.org/10.1111/ejss.12114_2, URL: https://bsssjournals.onlinelibrary.wiley.com/doi/10.1111/ejss.12114_2.

Baumberger, M., Haas, B., Sivakumar, S., Ludwig, M., Meyer, N., Meyer, H., 2024. High-resolution soil temperature and soil moisture patterns in space, depth and time: An interpretable machine learning modelling approach. Geoderma 451, 117049. http://dx.doi.org/10.1016/j.geoderma.2024.117049, URL: https://linkinghub.elsevier.com/retrieve/pii/S0016706124002787.

Baumberger, M., Haas, B., Tewes, W., Risse, B., Meyer, N., Meyer, H., 2025. Gated recurrent units for modelling time series of soil temperature and moisture: An assessment of performance and process reflectivity. Environ. Model. Softw. 183, 106245. http://dx.doi.org/10.1016/j.envsoft.2024.106245, URL: https://linkinghub.elsevier.com/retrieve/pii/S1364815224003062.

Bayerisches Landesamt für Umwelt, Germany, 2018a. Frankenwald, fichtelgebirge und vogtland. URL: https://www.lfu.bayern.de/boden/bodenreise/le_08.htm.

Bayerisches Landesamt für Umwelt, Germany, 2018b. Umweltatlas bayern. URL: https://www.umweltatlas.bayern.de.

Beillouin, D., Demenois, J., Cardinael, R., Berre, D., Corbeels, M., Fallot, A., Boyer, A., Feder, F., 2022. A global database of land management, land-use change and climate change effects on soil organic carbon. Sci. Data 9 (1), 228. http://dx.doi.org/10.1038/s41597-022-01318-1, URL: https://www.nature.com/articles/s41597-022-01318-1.

Berridge, D.M., Crouchley, R., 2011. Multivariate Generalized Linear Mixed Models Using R, 0 ed. CRC Press, http://dx.doi.org/10.1201/b10850, URL: https://www.taylorfrancis.com/books/9781439813270.

Bretas, I.L., Dubeux, J.C., Garcia, L., Queiroz, L.M., Lira, M.A., Ruiz-Moreno, M., Mendes, C.T., Zhou, T., Zhao, C., Trumpp, K.R., Oduor, K.T., 2025. Pedotransfer function for predicting deep-soil bulk density and assessing soil organic carbon and nitrogen stocks across land uses in coarse-textured soils. Catena 256, 109145. http://dx.doi.org/10.1016/j.catena.2025.109145, URL: https://linkinghub.elsevier.com/retrieve/pii/S0341816225004473.

Canadell, J., Jackson, R.B., Ehleringer, J.B., Mooney, H.A., Sala, O.E., Schulze, E.D., 1996. Maximum rooting depth of vegetation types at the global scale. Oecologia 108 (4), 583–595. http://dx.doi.org/10.1007/BF00329030, URL: http://link.springer.com/10.1007/BF00329030.

Coûteaux, M.M., Bottner, P., Anderson, J.M., Berg, B., Bolger, T., Casals, P., Romanyà, J., Thiéry, J.M., Vallejo, V.R., 2001. Decomposition of 13C-labelled standard plant material in a latitudinal transect of European coniferous forests: Differential impact of climate on the decomposition of soil organic matter compartments. Biogeochemistry 54 (2), 147–170. http://dx.doi.org/10.1023/A:1010613524551, URL: http://link.springer.com/10.1023/A:1010613524551.

Deng, L., Peng, C., Kim, D.G., Li, J., Liu, Y., Hai, X., Liu, Q., Huang, C., Shangguan, Z., Kuzyakov, Y., 2021. Drought effects on soil carbon and nitrogen dynamics in global natural ecosystems. Earth-Sci. Rev. 214, 103501. http://dx.doi.org/10.1016/j.earscirev.2020.103501, URL: https://linkinghub.elsevier.com/retrieve/pii/S001282522030547X.

Don, A., Schumacher, J., Scherer-Lorenzen, M., Scholten, T., Schulze, E.D., 2007. Spatial and vertical variation of soil carbon at two grassland sites — Implications for measuring soil carbon stocks. Geoderma 141 (3–4), 272–282. http://dx.doi.org/10.1016/j.geoderma.2007.06.003, URL: https://linkinghub.elsevier.com/retrieve/pii/S0016706107001711.

Dubeux, J.C., Lira Junior, M.D.A., Simili, F.F., Bretas, I.L., Trumpp, K.R., Bizzuti, B.E., Garcia, L., Oduor, K.T., Queiroz, L.M., Acuña, J.P., Mendes, C.T., 2024. Deep soil organic carbon: A review. CABI Rev. http://dx.doi.org/10.1079/cabireviews.2024.0024, URL: http://www.cabidigitallibrary.org/doi/10.1079/cabireviews.2024.0024. cabireviews.2024.0024.

Forstner, V., Groh, J., Vremec, M., Herndl, M., Vereecken, H., Gerke, H.H., Birk, S., Pütz, T., 2021. Response of water fluxes and biomass production to climate change in permanent grassland soil ecosystems. Hydrol. Earth Syst. Sci. 25 (12), 6087–6106. http://dx.doi.org/10.5194/hess-25-6087-2021, URL: https://hess.copernicus.org/articles/25/6087/2021/.

Hartig, F., 2022. DHARMa: Residual Diagnostics for Hierarchical (Multi-Level / Mixed) Regression Models. R package version 0.4.6, URL: https://github.com/florianhartig/dharma.

Hassink, J., The capacity of soils to preserve organic C and N by their association with clay and silt particles.

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., Marschner, B., 2018. Factors controlling the variability of organic matter in the top- and subsoil of a sandy dystric Cambisol under beech forest. Geoderma 311, 37–44. http://dx.doi.org/10.1016/j.geoderma.2017.09.028, URL: https://linkinghub.elsevier.com/retrieve/pii/S001670611731279X.

Jackson, R.B., Canadell, J., Ehleringer, J.R., Mooney, H.A., Sala, O.E., Schulze, E.D., 1996. A global analysis of root distributions for terrestrial biomes. Oecologia 108 (3), 389–411. http://dx.doi.org/10.1007/BF00333714, URL: http://link.springer.com/10.1007/BF00333714.

Jacobs, A., Poeplau, C., Weiser, C., Fahrion-Nitschke, A., Don, A., 2020. Exports and inputs of organic carbon on agricultural soils in Germany. Nutr. Cycl. Agroecosystems 118 (3), 249–271. http://dx.doi.org/10.1007/s10705-020-10087-5, URL: https://link.springer.com/10.1007/s10705-020-10087-5.

Jobbágy, E.G., Jackson, R.B., 2000. The vertical distribution of soil organic carbon and its relation to climate and vegetation. Ecol. Appl. 10 (2), 423–436. http://dx.doi.org/10.1890/1051-0761(2000)010[0423:TVDOSO]2.0.CO;2, URL: http://doi.wiley.com/10.1890/1051-0761(2000)010[0423:TVDOSO]2.0.CO;2.

Kögel-Knabner, I., Amelung, W., 2014. Dynamics, chemistry, and preservation of organic matter in soils. In: Treatise on Geochemistry. Elsevier, pp. 157–215. http://dx.doi.org/10.1016/B978-0-08-095975-7.01012-3, URL: https://linkinghub.elsevier.com/retrieve/pii/B9780080959757010123.

Kühnel, A., Garcia-Franco, N., Wiesmeier, M., Burmeister, J., Hobley, E., Kiese, R., Dannenmann, M., Kögel-Knabner, I., 2019. Controlling factors of carbon dynamics in grassland soils of Bavaria between 1989 and 2016. Agric. Ecosyst. Environ. 280, 118–128. http://dx.doi.org/10.1016/j.agee.2019.04.036, URL: https://linkinghub.elsevier.com/retrieve/pii/S0167880919301239.

Lal, R., 2004. Soil carbon sequestration impacts on global climate change and food security. Science 304 (5677), 1623–1627. http://dx.doi.org/10.1126/science.1097396, URL: https://www.science.org/doi/10.1126/science.1097396.

Lasisi, A.A., Akinremi, O.O., Tenuta, M., Cattani, D., 2018. Below-ground plant biomass and nitrogen uptake of perennial forage grasses and annual crops fertilized with pig manures. Agric. Ecosyst. Environ. 268, 1–7. http://dx.doi.org/10.1016/j.agee.2018.08.006, URL: https://linkinghub.elsevier.com/retrieve/pii/S0167880918303396.

Lenth, R.V., Piaskowski, J., 2025. emmeans: Estimated marginal means, aka least-squares means. URL: https://CRAN.R-project.org/package=emmeans.

Li, J., Wang, G., Mayes, M.A., Allison, S.D., Frey, S.D., Shi, Z., Hu, X.-M., Luo, Y., Melillo, J.M., 2019. Reduced carbon use efficiency and increased microbial turnover with soil warming. Global Change Biol. 25 (3), 900–910. http://dx.doi.org/10.1111/gcb.14517, URL: https://onlinelibrary.wiley.com/doi/10.1111/gcb.14517.

Linnenbrink, J., Milà, C., Ludwig, M., Meyer, H., 2024. kNNDM CV: k -fold nearest-neighbour distance matching cross-validation for map accuracy estimation. Geosci. Model. Dev. 17 (15), 5897–5912. http://dx.doi.org/10.5194/gmd-17-5897-2024, URL: https://gmd.copernicus.org/articles/17/5897/2024/.

Liu, Y., Guo, L., Jiang, Q., Zhang, H., Chen, Y., 2015. Comparing geospatial techniques to predict SOC stocks. Soil Tillage Res. 148, 46–58. http://dx.doi.org/10.1016/j.still.2014.12.002, URL: https://linkinghub.elsevier.com/retrieve/pii/S0167198714002670.

Lorenz, K., Lal, R., 2005. The depth distribution of soil organic carbon in relation to land use and management and the potential of carbon sequestration in subsoil horizons. In: Advances in Agronomy, vol. 88, Elsevier, pp. 35–66. http://dx.doi.org/10.1016/S0065-2113(05)88002-2, URL: https://linkinghub.elsevier.com/retrieve/pii/S0065211305880022.

Lundberg, S.M., Erion, G., Chen, H., DeGrave, A., Prutkin, J.M., Nair, B., Katz, R., Himmelfarb, J., Bansal, N., Lee, S.-I., 2020. From local explanations to global understanding with explainable AI for trees. Nat. Mach. Intell. 2 (1), 56–67. http://dx.doi.org/10.1038/s42256-019-0138-9, URL: https://www.nature.com/articles/s42256-019-0138-9.

Lundberg, S., Lee, S.I., 2017. A unified approach to interpreting model predictions. http://dx.doi.org/10.48550/ARXIV.1705.07874, URL: https://arxiv.org/abs/1705.07874. Version Number: 2.

Mayer, M., 2022. Shapviz: SHAP visualizations. R package version 0.10.3. URL: https://cran.r-project.org/web/packages/shapviz.

Mayer, S., Kühnel, A., Burmeister, J., Kögel-Knabner, I., Wiesmeier, M., 2019. Controlling factors of organic carbon stocks in agricultural topsoils and subsoils of Bavaria. Soil Tillage Res. 192, 22–32. http://dx.doi.org/10.1016/j.still.2019.04.021, URL: https://linkinghub.elsevier.com/retrieve/pii/S0167198719301187.

McGillycuddy, M., Warton, D.I., Popovic, G., Bolker, B.M., 2025. Parsimoniously fitting large multivariate random effects in glmmTMB. J. Stat. Softw. 112 (1), http://dx.doi.org/10.18637/jss.v112.i01, URL: https://www.jstatsoft.org/v112/i01/.

Meyer, H., Pebesma, E., 2021. Predicting into unknown space? Estimating the area of applicability of spatial prediction models. Methods Ecol. Evol. 12 (9), 1620–1633. http://dx.doi.org/10.1111/2041-210X.13650, URL: https://besjournals.onlinelibrary.wiley.com/doi/10.1111/2041-210X.13650.

Meyer, N., Welp, G., Amelung, W., 2018. The temperature sensitivity (Q10) of soil respiration: Controlling factors and spatial prediction at regional scale based on environmental soil classes. Glob. Biogeochem. Cycles 32 (2), 306–323. http://dx.doi.org/10.1002/2017GB005644, URL: http://doi.wiley.com/10.1002/2017GB005644.

Milà, C., Mateu, J., Pebesma, E., Meyer, H., 2022. Nearest neighbour distance matching leave-one-out cross-validation for map validation. Methods Ecol. Evol. 13 (6), 1304–1316. http://dx.doi.org/10.1111/2041-210X.13851, URL: https://besjournals.onlinelibrary.wiley.com/doi/10.1111/2041-210X.13851.

Monti, A., Zatta, A., 2009. Root distribution and soil moisture retrieval in perennial and annual energy crops in Northern Italy. Agric. Ecosyst. Environ. 132 (3–4), 252–259. http://dx.doi.org/10.1016/j.agee.2009.04.007, URL: https://linkinghub.elsevier.com/retrieve/pii/S0167880909001108.

Mueller, C.W., Koegel-Knabner, I., 2009. Soil organic carbon stocks, distribution, and composition affected by historic land use changes on adjacent sites. Biol. Fertil. Soils 45 (4), 347–359. http://dx.doi.org/10.1007/s00374-008-0336-9, URL: http://link.springer.com/10.1007/s00374-008-0336-9.

Muñoz-Rojas, M., Jordán, A., Zavala, L.M., De La Rosa, D., Abd-Elmabod, S.K., Anaya-Romero, M., 2012. Organic carbon stocks in Mediterranean soil types under different land uses (Southern Spain). Solid Earth 3 (2), 375–386. http://dx.doi.org/10.5194/se-3-375-2012, URL: https://se.copernicus.org/articles/3/375/2012/.

Oppong Sarkodie, V.Y., Vašát, R., Pouladi, N., Šrámek, V., Sáňka, M., Fadrhonsová, V., Hellebrandová, K.N., Borůvka, L., 2023. Predicting soil organic carbon stocks in different layers of forest soils in the Czech Republic. Geoderma Reg. 34, e00658. http://dx.doi.org/10.1016/j.geodrs.2023.e00658, URL: https://linkinghub.elsevier.com/retrieve/pii/S2352009423000548.

Paltineanu, C., Dumitru, S., Vizitiu, O., Mocanu, V., Lăcătusu, A.R., Ion, S., Domnariu, H., 2024. Soil organic carbon and total nitrogen stocks related to land use and basic environmental properties - assessment of soil carbon sequestration potential in different ecosystems. Catena 246, 108435. http://dx.doi.org/10.1016/j.catena.2024.108435, URL: https://linkinghub.elsevier.com/retrieve/pii/S0341816224006325.

Paustian, K., Larson, E., Kent, J., Marx, E., Swan, A., 2019. Soil c sequestration as a biological negative emission strategy. Front. Clim. 1, 8. http://dx.doi.org/10.3389/fclim.2019.00008, URL: https://www.frontiersin.org/article/10.3389/fclim.2019.00008/full.

Poeplau, C., Don, A., 2013. Sensitivity of soil organic carbon stocks and fractions to different land-use changes across Europe. Geoderma 192, 189–201. http://dx.doi.org/10.1016/j.geoderma.2012.08.003, URL: https://linkinghub.elsevier.com/retrieve/pii/S0016706112002984.

Poeplau, C., Jacobs, A., Don, A., Vos, C., Schneider, F., Wittnebel, M., Tiemeyer, B., Heidkamp, A., Prietz, R., Flessa, H., 2020. Stocks of organic carbon in German agricultural soils—Key results of the first comprehensive inventory. J. Plant Nutr. Soil Sci. 183 (6), 665–681. http://dx.doi.org/10.1002/jpln.202000113, URL: https://onlinelibrary.wiley.com/doi/10.1002/jpln.202000113.

Poeplau, C., Vos, C., Don, A., 2017. Soil organic carbon stocks are systematically overestimated by misuse of the parameters bulk density and rock fragment content. Soil 3 (1), 61–66. http://dx.doi.org/10.5194/soil-3-61-2017, URL: https://soil.copernicus.org/articles/3/61/2017/.

Poeplau, C., Zopf, D., Greiner, B., Geerts, R., Korvaar, H., Thumm, U., Don, A., Heidkamp, A., Flessa, H., 2018. Why does mineral fertilization increase soil carbon stocks in temperate grasslands? Agric. Ecosyst. Environ. 265, 144–155. http://dx.doi.org/10.1016/j.agee.2018.06.003, URL: https://linkinghub.elsevier.com/retrieve/pii/S0167880918302378.

Puhe, J., 1994. Die Wurzelentwicklung der Fichte (Picea abies [L.] Karst.) bei unterschiedlichen chemischen Bodenbedingungen. Forschungszentrum Waldökosysteme University Göttingen, Göttingen.

R. Core Team, 2021. R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria, URL: https://www.R-project.org/.

Reicosky, D., Kemper, W., Langdale, G., Douglas, C., Rasmussen, P., 1995. Soil organic matter changes resulting from tillage and biomass production. J. Soil Water Conserv. 50 (3), 253–261. http://dx.doi.org/10.1080/00224561.1995.12456959, URL: https://www.tandfonline.com/doi/full/10.1080/00224561.1995.12456959.

Rial, M., Martínez Cortizas, A., Rodríguez-Lado, L., 2017. Understanding the spatial distribution of factors controlling topsoil organic carbon content in European soils. Sci. Total Environ. 609, 1411–1422. http://dx.doi.org/10.1016/j.scitotenv.2017.08.012, URL: https://linkinghub.elsevier.com/retrieve/pii/S0048969717320107.

Rösch, M., Hahne, J., 2024. Fichtelgebirge. In: Feeser, I., Dörfler, W., Rösch, M., Jahns, S., Wolters, S., Bittmann, F. (Eds.), Vegetationsgeschichte der Landschaften in Deutschland. Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 391–396. http://dx.doi.org/10.1007/978-3-662-68936-3_45, URL: https://link.springer.com/10.1007/978-3-662-68936-3_45.

Rumpel, C., Kögel-Knabner, I., 2011. Deep soil organic matter—a key but poorly understood component of terrestrial C cycle. Plant Soil 338 (1–2), 143–158. http://dx.doi.org/10.1007/s11104-010-0391-5, URL: http://link.springer.com/10.1007/s11104-010-0391-5.

Ryo, M., Rillig, M.C., 2017. Statistically reinforced machine learning for nonlinear patterns and variable interactions. Ecosphere 8 (11), e01976. http://dx.doi.org/10.1002/ecs2.1976, URL: https://esajournals.onlinelibrary.wiley.com/doi/10.1002/ecs2.1976.

Schubert, A., 2010. Bodendauerbeobachtung, Bodeninventur, Bodenzustandserhebung (BZE 2). LWF Bayern, Germany, München.

Silver, W.L., Miya, R.K., 2001. Global patterns in root decomposition: comparisons of climate and litter quality effects. Oecologia 129 (3), 407–419. http://dx.doi.org/10.1007/s004420100740, URL: http://link.springer.com/10.1007/s004420100740.

Solly, E.F., Schöning, I., Boch, S., Kandeler, E., Marhan, S., Michalzik, B., Müller, J., Zscheischler, J., Trumbore, S.E., Schrumpf, M., 2014. Factors controlling decomposition rates of fine root litter in temperate forests and grasslands. Plant Soil 382 (1–2), 203–218. http://dx.doi.org/10.1007/s11104-014-2151-4, URL: http://link.springer.com/10.1007/s11104-014-2151-4.

Sørensen, R., Zinko, U., Seibert, J., 2006. On the calculation of the topographic wetness index: evaluation of different methods based on field observations. Hydrol. Earth Syst. Sci.

Sponagel, H., Ad-hoc-Arbeitsgruppe Boden der Staatlichen Geologischen Dienste und der Bundesanstalt für Geowissenschaften und Rohstoffe, Bundesanstalt für Geowissenschaften und Rohstoffe (Eds.), 2005. Bodenkundliche kartieranleitung: mit 41 abbildungen, 103 tabellen und 31 listen, 5., verbesserte und erweiterte Auflage ed. Bundesanst. für Geowiss. und Rohstoffe, Hannover.

Taylor, A.R., Lenoir, L., Vegerfors, B., Persson, T., 2019. Ant and earthworm Bioturbation in cold-temperate ecosystems. Ecosystems 22 (5), 981–994. http://dx.doi.org/10.1007/s10021-018-0317-2, URL: http://link.springer.com/10.1007/s10021-018-0317-2.

Todd-Brown, K.E.O., Randerson, J.T., Post, W.M., Hoffman, F.M., Tarnocai, C., Schuur, E.A.G., Allison, S.D., 2013. Causes of variation in soil carbon simulations from CMIP5 earth system models and comparison with observations. Biogeosciences 10 (3), 1717–1736. http://dx.doi.org/10.5194/bg-10-1717-2013, URL: https://bg.copernicus.org/articles/10/1717/2013/.

Torppa, K.A., Taylor, A.R., 2022. Alternative combinations of tillage practices and crop rotations can foster earthworm density and bioturbation. Appl. Soil Ecol. 175, 104460. http://dx.doi.org/10.1016/j.apsoil.2022.104460, URL: https://linkinghub.elsevier.com/retrieve/pii/S0929139322000762.

Vos, C., Don, A., Hobley, E.U., Prietz, R., Heidkamp, A., Freibauer, A., 2019. Factors controlling the variation in organic carbon stocks in agricultural soils of Germany. Eur. J. Soil Sci. 70 (3), 550–564. http://dx.doi.org/10.1111/ejss.12787, URL: https://bsssjournals.onlinelibrary.wiley.com/doi/10.1111/ejss.12787.

Wellbrock, N., Bolte, A. (Eds.), 2019. Status and dynamics of forests in germany: results of the national forest monitoring. In: Ecological Studies, vol. 237, Springer International Publishing, Cham, http://dx.doi.org/10.1007/978-3-030-15734-0, URL: http://link.springer.com/10.1007/978-3-030-15734-0.

Wickham, H., 2016. ggplot2: elegant graphics for data analysis, second ed. In: Use R!, Springer international publishing, Cham.

Wiesmeier, M., Hübner, R., Barthold, F., Spörlein, P., Geuß, U., Hangen, E., Reischl, A., Schilling, B., Von Lützow, M., Kögel-Knabner, I., 2013a. Amount, distribution and driving factors of soil organic carbon and nitrogen in cropland and grassland soils of southeast Germany (Bavaria). Agric. Ecosyst. Environ. 176, 39–52. http://dx.doi.org/10.1016/j.agee.2013.05.012, URL: https://linkinghub.elsevier.com/retrieve/pii/S016788091300162X.

Wiesmeier, M., Lützow, M.V., Spörlein, P., Geuß, U., Hangen, E., Reischl, A., Schilling, B., Kögel-Knabner, I., 2015. Land use effects on organic carbon storage in soils of Bavaria: The importance of soil types. Soil Tillage Res. 146, 296–302. http://dx.doi.org/10.1016/j.still.2014.10.003, URL: https://linkinghub.elsevier.com/retrieve/pii/S0167198714002049.

Wiesmeier, M., Poeplau, C., Sierra, C.A., Maier, H., Frühauf, C., Hübner, R., Kühnel, A., Spörlein, P., Geuß, U., Hangen, E., Schilling, B., Von Lützow, M., Kögel-Knabner, I., 2016. Projected loss of soil organic carbon in temperate agricultural soils in the 21st century: effects of climate change and carbon input trends. Sci. Rep. 6 (1), 32525. http://dx.doi.org/10.1038/srep32525, URL: https://www.nature.com/articles/srep32525.

Wiesmeier, M., Prietzel, J., Barthold, F., Spörlein, P., Geuß, U., Hangen, E., Reischl, A., Schilling, B., Von Lützow, M., Kögel-Knabner, I., 2013b. Storage and drivers of organic carbon in forest soils of southeast Germany (Bavaria) – implications for carbon sequestration. Forest Ecol. Manag. 295, 162–172. http://dx.doi.org/10.1016/j.foreco.2013.01.025, URL: https://linkinghub.elsevier.com/retrieve/pii/S0378112713000698.

Wiesmeier, M., Spörlein, P., Geuß, U., Hangen, E., Haug, S., Reischl, A., Schilling, B., Von Lützow, M., Kögel-Knabner, I., 2012. Soil organic carbon stocks in southeast Germany (Bavaria) as affected by land use, soil type and sampling depth. Global Change Biol. 18 (7), 2233–2245. http://dx.doi.org/10.1111/j.1365-2486.2012.02699.x, URL: https://onlinelibrary.wiley.com/doi/10.1111/j.1365-2486.2012.02699.x.

Wiesmeier, M., Urbanski, L., Hobley, E., Lang, B., Von Lützow, M., Marin-Spiotta, E., Van Wesemael, B., Rabot, E., Ließ, M., Garcia-Franco, N., Wollschläger, U., Vogel, H.-J., Kögel-Knabner, I., 2019. Soil organic carbon storage as a key function of soils - A review of drivers and indicators at various scales. Geoderma 333, 149–162. http://dx.doi.org/10.1016/j.geoderma.2018.07.026, URL: https://linkinghub.elsevier.com/retrieve/pii/S0016706117319845.

Wright, M.N., Ziegler, A., 2017. **ranger** : A fast implementation of random forests for high dimensional data in *C++* and *R*. J. Stat. Softw. 77 (1), http://dx.doi.org/10.18637/jss.v077.i01, URL: http://www.jstatsoft.org/v77/i01/.

Xiao, J., Lin, Y., He, X., He, Z., Kong, X., 2023. Drought exerted a stronger controlling effect on soil carbon release than moisturizing in a global meta-analysis. Forests 14 (10), 1957. http://dx.doi.org/10.3390/f14101957, URL: https://www.mdpi.com/1999-4907/14/10/1957.

Yigini, Y., Panagos, P., 2016. Assessment of soil organic carbon stocks under future climate and land cover changes in Europe. Sci. Total Environ. 557–558, 838–850. http://dx.doi.org/10.1016/j.scitotenv.2016.03.085, URL: https://linkinghub.elsevier.com/retrieve/pii/S0048969716305095.