The impact of agricultural management on soil aggregation and carbon storage is regulated by climatic thresholds across a 3000 km European gradient

Author(s):
Edlinger, Anna; Garland, Gina; Banerjee, Samiran; Degrune, Florine; García-Palacios, Pablo; Herzog, Chantal; Sánchez Pescador, David; Romdhane, Sana; Ryo, Masahiro; Saghaï, Aurélien; Hallin, Sara; Maestre, Fernando T.; Philippot, Laurent; Rillig, Matthias C.; van der Heijden, Marcel G.A.

Publication date:
2023-06

Permanent link:
https://doi.org/10.3929/ethz-b-000607844

Originally published in:
Global Change Biology 29(11), https://doi.org/10.1111/gcb.16677

Received: 24 June 2022 | Accepted: 7 February 2023
DOI: 10.1111/gcb.16677

RESEARCH ARTICLE

Global Change Biology WILEY

The impact of agricultural management on soil aggregation and carbon storage is regulated by climatic thresholds across a 3000 km European gradient

Anna Edlinger[1,2] | Gina Garland[1,3] | Samiran Banerjee[4] | Florine Degrune[5,6,7] | Pablo García-Palacios[8] | Chantal Herzog[1,2] | David Sánchez Pescador[9] | Sana Romdhane[10] | Masahiro Ryo[5,6,11,12] | Aurélien Saghaï[13] | Sara Hallin[13] | Fernando T. Maestre[14,15] | Laurent Philippot[10] | Matthias C. Rillig[5,6] | Marcel G. A. van der Heijden[1,2]

[1]Agroscope, Plant-Soil Interactions Group, Zurich, Switzerland
[2]Department of Plant and Microbial Biology, University of Zurich, Zurich, Switzerland
[3]Department of Environmental System Science, ETH Zurich, Zurich, Switzerland
[4]Department of Microbiological Sciences, North Dakota State University, Fargo, North Dakota, USA
[5]Institute of Biology, Freie Universität Berlin, Berlin, Germany
[6]Berlin-Brandenburg Institute of Advanced Biodiversity Research (BBIB), Berlin, Germany
[7]Soil Science and Environment Group, Changins, University of Applied Sciences and Arts Western Switzerland, Nyon, Switzerland
[8]Instituto de Ciencias Agrarias, Consejo Superior de Investigaciones Científicas, Madrid, Spain
[9]Departamento de Biología y Geología, Física y Química Inorgánica, Escuela Superior de Ciencias Experimentales y Tecnología, Universidad Rey Juan Carlos, Móstoles, Spain
[10]Department of Agroecology, INRA, AgroSup Dijon, University Bourgogne Franche Comte, Dijon, France
[11]Leibniz Centre for Agricultural Landscape Research (ZALF), Müncheberg, Germany
[12]Brandenburg University of Technology Cottbus-Senftenberg, Cottbus, Germany
[13]Department of Forest Mycology and Plant Pathology, Swedish University of Agricultural Sciences, Uppsala, Sweden
[14]Instituto Multidisciplinar para el Estudio del Medio "Ramón Margalef", Universidad de Alicante, Alicante, Spain
[15]Departamento de Ecología, Universidad de Alicante, Alicante, Spain

Correspondence
Anna Edlinger and Marcel G. A. van der Heijden, Agroscope, Plant-Soil Interactions Group, 8046 Zurich, Switzerland.
Email: anna.edlinger@wur.nl and marcel.vanderheijden@agroscope.admin.ch,

Present address
Anna Edlinger, Pant Sciences Group, Wageningen University and Research, 6708 PB, Wageningen, The Netherlands

Abstract

Organic carbon and aggregate stability are key features of soil quality and are important to consider when evaluating the potential of agricultural soils as carbon sinks. However, we lack a comprehensive understanding of how soil organic carbon (SOC) and aggregate stability respond to agricultural management across wide environmental gradients. Here, we assessed the impact of climatic factors, soil properties and agricultural management (including land use, crop cover, crop diversity, organic fertilization, and management intensity) on SOC and the mean weight diameter of soil aggregates, commonly used as an indicator for soil aggregate stability, across a 3000 km European gradient. Soil aggregate stability (−56%) and SOC stocks

Funding information
Agence Nationale de la Recherche, Grant/Award Number: ANR-16-EBI3-0004-01; Biodiversa+; Deutsche Forschungsgemeinschaft, Grant/Award Number: 317895346; Ministerio de Economía y Competitividad, Grant/Award Number: PCIN-2016-028; Schweizerischer Nationalfonds zur Förderung der Wissenschaftlichen Forschung, Grant/Award Number: 31BD30-172462; Svenska Forskningsrådet Formas, Grant/Award Number: 2016-0194

(−35%) in the topsoil (20 cm) were lower in croplands compared with neighboring grassland sites (uncropped sites with perennial vegetation and little or no external inputs). Land use and aridity were strong drivers of soil aggregation explaining 33% and 20% of the variation, respectively. SOC stocks were best explained by calcium content (20% of explained variation) followed by aridity (15%) and mean annual temperature (10%). We also found a threshold-like pattern for SOC stocks and aggregate stability in response to aridity, with lower values at sites with higher aridity. The impact of crop management on aggregate stability and SOC stocks appeared to be regulated by these thresholds, with more pronounced positive effects of crop diversity and more severe negative effects of crop management intensity in nondryland compared with dryland regions. We link the higher sensitivity of SOC stocks and aggregate stability in nondryland regions to a higher climatic potential for aggregate-mediated SOC stabilization. The presented findings are relevant for improving predictions of management effects on soil structure and C storage and highlight the need for site-specific agri-environmental policies to improve soil quality and C sequestration.

KEYWORDS
aggregate stability, agro-ecosystems, aridity, climatic threshold, environmental gradient, intensive agriculture, soil organic carbon

1 | INTRODUCTION

Soils store more carbon (C) than plants and the atmosphere combined (Jackson et al., 2017; Köchy et al., 2015). Finding ways to increase soil organic carbon (SOC) stocks is not only an important climate change mitigation strategy (Crowther et al., 2016) but also a key approach to improve the delivery of multiple ecosystem services (Chenu et al., 2019; Wiesmeier et al., 2019). Agricultural soils store more than 140 Pg C in the top 30 cm (Zomer et al., 2017). This accounts for 19% of the global SOC stocks estimated at this soil depth (Foley et al., 2011; Jackson et al., 2017), which is not only the most relevant soil layer for agricultural production but also heavily impacted by the management of these systems, causing an ongoing loss of SOC from agricultural soils (Keel et al., 2019; Sanderman et al., 2017; Smith, 2008). This trend will likely increase under increasing temperatures, fueling accelerated decomposition of SOC, particularly in temperate regions (Crowther et al., 2016; Wiesmeier et al., 2016). As such, there is a growing need to evaluate the potential impacts of soil management practices across contrasting environmental conditions, which will ultimately help to find solutions that can simultaneously address climate change mitigation and food security (Lal, 2004).

Soil aggregate stability, or the ability of soils to withstand physical forces, is interlinked with SOC (Wiesmeier et al., 2019), and has been identified as a major indicator of soil quality and fertility (Bünemann et al., 2018; Garland et al., 2021; Lehmann et al., 2020). This is not only because of its role in stabilizing the soil matrix and storing SOC (Tisdall & Oades, 1982) but also because of its sensitivity to changes in land use and soil management (Or et al., 2021). The complex dynamics of soil aggregation and physical soil organic matter stabilization are impacted by a range of intrinsic and external factors. In addition to abiotic drivers, plants and soil biota play an integral role in the formation and stabilization of soil aggregates and SOC (Beare et al., 1997; Lehmann et al., 2017; Six, Feller, et al., 2002). Thus, although soil aggregate formation and turnover are largely determined by pedoclimatic factors (Bronick & Lal, 2005; Or et al., 2021; Wiesmeier et al., 2019). For example, soils in grasslands are known to be more aggregated (Elliott, 2010; Williams et al., 2020) and richer in SOC than in cultivated lands (Guo & Gifford, 2002). In arable systems, no-till farming can promote aggregate stability, and several studies have identified the accumulation of SOC in aggregate pools as a significant driver of C accrual during the conversion from conventional till to no-till systems (Singh et al., 2020; Six et al., 1999, 2000) or following periods of ley in the crop rotation (Guest et al., 2022). In addition, continuous soil cover can enhance soil aggregation and SOC storage compared with systems with bare fallow periods in dryland farming (Rosenzweig et al., 2018). More diverse crop rotations can also promote soil aggregation and SOC accumulation through interactions with the microbial community in specific agricultural contexts (McDaniel et al., 2014; Tiemann et al., 2015). However, studies investigating the effect of land use or agricultural management practices on soil aggregation and SOC protection commonly focus on factorial comparisons of isolated management practices (e.g., till vs. no-till, conventional vs. organic, monoculture vs. crop rotation; Bai et al., 2018; Mäder et al., 2002; McDaniel et al., 2014; Rosenzweig et al., 2018) or are limited to a narrow biogeographical context (Keel et al., 2019; Williams et al., 2020). While these studies allow for a controlled assessment of specific management practices under a given set of local constraints, they cannot be used to understand the relative importance of different management practices in relation to a broader range of climatic and soil properties.

The growing evidence showing that the influence of climate, and particularly aridity, on several soil properties can be characterized by abrupt or nonlinear changes in certain ecosystems (Berdugo et al., 2020; Feng et al., 2022), calls for studies examining interactions between potential climatic thresholds with agricultural management. For example, the occurrence of aridity thresholds for various soil properties, including SOC, in global drylands has been observed by Berdugo et al. (2020). However, we do not know whether we can expect abrupt changes in aggregate stability and SOC also in agricultural soils, or whether climatic thresholds determine the sensitivity of soil properties to soil management. Addressing these knowledge gaps is highly relevant for appropriate predictions of soil management effects on soil structure and SOC storage, as well as for targeted agri-environmental policies.

Here we report results from a large-scale observational study across a 3000 km gradient in Europe spanning from Sweden to Spain and comprising a total of 162 field soils (104 cropland soils and 58 soils originating from adjacent marginal land and grasslands). We aimed to (1) compare soil aggregate stability, SOC pools and SOC stocks across different land uses (cropland vs. uncropped sites), (2) assess the relative contribution of management intensity, climate, and soil properties to aggregate stability and SOC storage, and (3) explore potential nonlinearity and interactions of these drivers on soil aggregation and SOC. We hypothesized that soil aggregate stability and SOC stocks are mainly regulated by inherent soil and climatic factors, but that agricultural management acts as an important driver within distinct location-specific contexts. Moreover, we expect to observe threshold-like relationships between climatic factors and the investigated soil properties and assume that such thresholds determine the interaction effects of climate and agricultural management on SOC and aggregation.

2 | MATERIALS AND METHODS

2.1 | Field sites

We selected 104 cropland sites and 58 adjacent noncropped sites across a North–South gradient in Europe including sites in Sweden ($n = 21$), Germany ($n = 40$), Switzerland ($n = 39$), France ($n = 30$), and Spain ($n = 32$; Figure 1). For this study, we focused on a subset of the initially sampled arable sites ($n = 155$) used in Garland et al. (2021), as outlined in Appendix S1. Sampling took place during the spring of 2017. To minimize variation caused by different crop types, we selected arable fields planted with wheat (*Triticum sp.*, $n = 80$), or closely related cereals like barley (*Hordeum vulgare*, $n = 21$) and oat (*Avena sativa*, $n = 3$), when wheat fields were not available. Furthermore, we targeted plots where conventional tilling practices had been used throughout the previous year. In each country, we selected arable

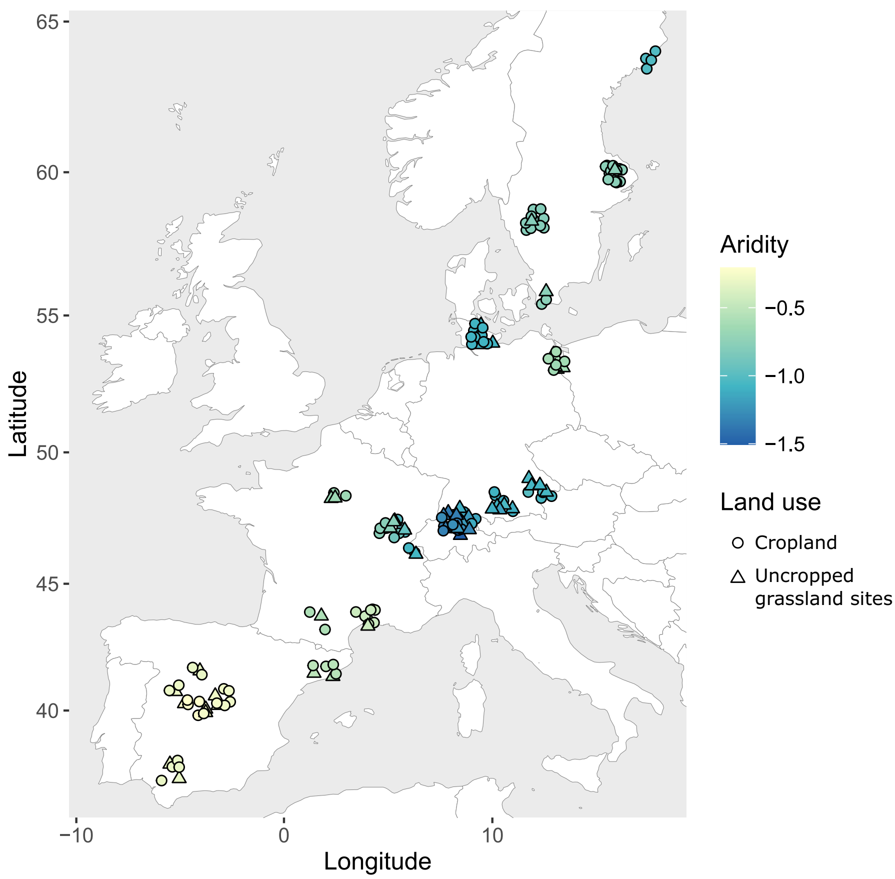


FIGURE 1 Croplands and uncropped grassland sites sampled across a European trans-continental gradient. The colors ranging from yellow to dark blue represent a gradient in aridity from high to low values (aridity = 1-aridity index, unitless). Map lines delineate study areas and do not necessarily depict accepted national boundaries.

fields that varied in crop rotational diversity, that is, with differing numbers of crop species over a 10-year crop rotation, to be able to determine whether crop diversification influences soil aggregate stability and SOC storage. Moreover, the selected arable fields varied in management intensity related to tillage, fertilizer and pesticide application, and we obtained such information using questionnaires at each site (Garland et al., 2021). The noncropped sites were located in the vicinity of the croplands to cover similar soil characteristics and served as a benchmark for the approximate potential for soil aggregation and SOC storage. These sites comprised extensively managed grasslands and marginal land (field strips) neighbouring the croplands that were characterized by a permanent, predominantly herbaceous plant cover that was not part of a crop rotation. Most of these sites were unfertilized and occasionally mowed, although the exact information on fertilization, grazing and mowing was not available for all sites. Following the classification by the Eurostat Land Use/Cover Area Frame Survey (LUCAS; Eurostat, 2018), we refer to these plots as grassland sites hereafter.

2.2 | Climate information

To characterize the variation in climate along the sampled gradient, information on mean annual temperature (MAT) and mean annual precipitation (MAP) was extracted from the WorldClim Global Climate Data (Fick & Hijmans, 2017), which is a high-resolution global geo-database of monthly average data (1950–2000) based on a high number of climate observations and SRTM (Shuttle Radar Topography Mission) topographical data. Additionally, climate variability was represented by temperature and precipitation seasonality, that is, the coefficient of variation of monthly temperature and precipitation, respectively. The aridity index (AI) was derived from the CGIAR-CSI database which uses climate data related to evapotranspiration processes and rainfall deficit for potential vegetative growth (Trabucco & Zomer, 2019). We calculated aridity as 1 minus AI following Berdugo et al. (2020) and García-Palacios et al. (2018) so that higher aridity values indicate drier conditions. Aridity was highly correlated with annual precipitation ($\rho = -0.93$) and less with MAT ($\rho = 0.47$; Table S2) and had a curve-shaped distribution along the sampled gradient, with highest aridity values in Spain, and lowest values in Switzerland (Figure S2a). The MAT decreased gradually from southern to northern countries (Figure S2b).

2.3 | Soil sampling and analyses

To reduce the variation in soil properties due to different developmental stages of plants and the associated management practices, soil samples were collected around flowering time (ranging from May in Spain to August in Northern Sweden). At each site, eight soil cores were taken in a circular pattern within a 10 m radius using a 5 cm diameter auger and to a depth of 20 cm. Three of the soil cores were kept intact and stored at 4°C before using them to assess aggregate stability and bulk density. The other soil cores were homogenized and sieved to 2 mm. A portion of this soil was air-dried for further processing of soil physical and chemical analyses. Soil texture was assessed by measuring sedimentation of suspended soil particles at different time intervals in an aqueous solution after humus oxidation. The soil pH was measured with H_2O using a 1:2 soil: water ratio. SOC was determined by a potassium dichromate-sulfuric acid wet oxidation method with back-titration with ferrous sulphate. Exchangeable calcium and magnesium were assessed by atomic spectrometry following extraction of the samples with a barium chloride/triethanolamine solution buffered to pH 8.1 (Swiss Federal Research Stations, 1996).

2.4 | Soil aggregate stability and SOC

For estimations of bulk density, the intact soil cores were weighed, and the soil moisture was recorded from a subsample after homogenization of the soil by gently removing stones and residues larger than 8 mm. The bulk density of the remaining soil was calculated by subtracting the mass and volume of these large fragments from the total dry mass and volume of the collected soil cores and served as a basis for the estimation of SOC stocks. The volume of the stones was determined by water displacement in a graduated cylinder (Corti et al., 1998). The air-dried, 8 mm sieved soil was subsequently used to measure aggregate stability by applying a wet sieving method, coupled with a correction for aggregate-sized sand to obtain the sand-free aggregates by subtracting the mass content of sand particles in each aggregate fraction (i.e., >53 μm in the free microaggregate fraction, >250 μm in the small and >2000 μm in the large macroaggregate fraction, respectively; Six et al., 1998). This technique is commonly employed to assess the impacts of soil aggregation on organic matter dynamics, as the aggregates which resist the integral slaking step are known to be more stable than other methods used to assess aggregation, and thus are more likely to be involved with carbon stabilization mechanisms (Elliott, 1986). The large macroaggregate (>2000 μm), small macroaggregate (250–2000 μm), free microaggregate (53–250 μm) and free silt and clay fraction (<53 μm) were collected. The mean weight diameter (MWD) of aggregate fractions, a commonly used index to describe the stability of soil aggregates, was calculated using Equation (1):

$$\mathrm{MWD} = \sum_i P_i S_i \tag{1}$$

where S_i is the average diameter (μm) of the ith fraction (i.e., macroaggregate, microaggregate, etc.) and P_i the mass proportion of the ith fraction using the sand-free base (van Bavel, 1950).

SOC within each aggregate fraction was measured using the potassium dichromate-sulphuric acid wet oxidation method as described above (Swiss Federal Research Stations, 1996). The amount of aggregate associated SOC was calculated as SOC concentration within each fraction multiplied by the uncorrected proportion of the fraction (Edlinger et al., 2023) and was expressed as g of aggregate associated SOC per kg of dry soil.

SOC stocks were calculated for the 0–20 cm depth increment based on the mass of soil particles smaller than 8 mm using a minimum equivalent soil mass approach (Ellert & Bettany, 1995; Lee et al., 2009) following the formulas described by Poeplau et al. (2017) and Schiedung et al. (2019). We chose an equivalent soil mass rather than volume-based approach to estimate SOC stocks because this allows for comparisons of SOC stored within a defined mass of soil across different locations and land-use types, irrespective of influences of management on bulk density (Wendt & Hauser, 2013). The calculation steps are further outlined in Appendix S2. Values should be interpreted carefully since SOC was analyzed on 2 mm sieved soil and SOC stock estimates could not be corrected for stones 2–8 mm, which could lead to an overestimation of SOC stocks. This does not affect the interpretation of patterns observed in this study but needs to be considered when comparing presented SOC stocks with other studies.

2.5 | Crop management

To determine the relative effects of crop management on soil aggregation and SOC storage in the arable fields, we collected information on several crop management parameters, including crop diversity, the duration of crop cover, fertilizer and pesticide use, tillage, and overall management intensity (range and units in Table S1).

To consider the legacy effect of crop species cultivated in each site, both the proportion of time with crop cover and the level of crop diversity were calculated considering the last 10 years before the field sampling. The proportion of time with crop cover was defined as the number of months with living plants covering the soil divided by the total number of months in the crop rotation period. Crop diversification was evaluated by using a modified Shannon index, a measure of crop evenness during the 10 years of crop rotation, following Garland et al. (2021; Appendix S3).

Considering the range of different management practices performed in each site across environmental gradient (Edlinger et al., 2023), we created a single variable to describe management intensity which could then be compared across sites. This included data on the number of pesticide (fungicide, herbicide, and insecticide) application events, the amount of mineral nitrogen (N) applied, and the number and maximum depth of tillage events from the 2017 growing season. To aggregate these different practices into one index, the individual management variables were normalized by calculating *z*-scores, which were then averaged to attain an overall management intensity index. *Z*-scores were calculated as $z = (x - \mu)/\sigma$, where x is the raw score to be standardized, μ the mean of the variable, and σ the standard deviation of the variable. Individual missing crop management values were replaced with the median of the respective management value of each country, prior to calculating the management intensity index.

Organic fertilization reflected organic fertilizer application during 1 year before the field sampling and was represented as a binary variable (i.e., 1 when organic fertilizers were used at least once during 12 months previous to sampling, 0 if no organic fertilizers were used during this period of time).

2.6 | Statistical analyses

All statistical analyses were performed using the R statistical program (R Core Team, 2018, version 3.5.3). We applied different machine learning techniques to evaluate the relative importance of and interactions between the different variables (e.g., climate, management, and soil properties) to explain soil aggregation and SOC. The script used for the permutation-based random forest, partial-dependence plots and model-based trees was adapted from Ryo and Rillig (2017) and is available at https://doi.org/10.6084/m9.figshare.19762039.

2.6.1 | Grouping according to high and low aridity and clay content

We explored the differences in the relative amount of water-stable aggregate fractions and the fraction-associated SOC along the climatic and soil texture gradient. To do so, we grouped the sampled sites according to their aridity and clay content, into "high" and "low" aridity as well as "high" and "low" clay content groups following the Jenks' natural breaks approach (Jenks, 1967) using the R package *BAMMtools* (version 2.1.10; Rabosky et al., 2014). This approach forms optimal groups based on data distribution to reduce variation in aridity and clay within groups and increase variation between groups.

2.6.2 | Random forests algorithm with variable selection

To estimate the relative importance of site-specific versus management factors influencing aggregate stability and SOC, we first applied a random forest algorithm (Breiman, 2001), using the R package *randomForest* version 4.6.14 (Liaw & Wiener, 2002). Random forest models are increasingly applied in ecological studies (Banerjee et al., 2019; Delgado-Baquerizo et al., 2016). They allow the modeling of nonlinear relationships between response and explanatory variables and are less prone to suffer from collinearity between predictors compared with parametric statistical models. We examined the best predictors for aggregate stability and SOC independently, using a set of pre-selected climatic factors, physicochemical soil properties, and soil management practices (Table S2) that are known to influence SOC storage and aggregation (Bronick & Lal, 2005; Wiesmeier et al., 2019). Even though tree-based models like random forests are less prone to issues of multi-collinearity than regression-based models, we tried to avoid strong correlations between predictors (i.e., $\rho > 0.80$) to allow for a representative relative importance estimate. This pre-selection resulted in a total of four climate variables (aridity, MAT, temperature seasonality, and precipitation seasonality), five abiotic properties (clay, silt, Ca and Mg content, pH) to explain variation in SOC and soil aggregation in the two land use types assessed. To account for the additional variation in cropland fields, four predictors describing crop management were included (crop diversity, crop cover, management intensity, and organic fertilization). Additionally, we included the spatial location along the sampled gradient (despite a strong correlation between the geographic location and climate) in the analysis to account for additional variation that was not accounted for by the other variables such as soil mineralogy but attributable to spatial autocorrelation (Mascaro et al., 2014). We set the hyperparameters to 2000 permutation steps, 100 trees, and the others as defaults (Figure S4; Ryo & Rillig, 2017).

2.6.3 | Identifying key predictors and their associations with the responses

The relative importance of predictors was measured by evaluating how much each predictor contributed to increasing the model accuracy. To do so, we first conducted variable selection based on the approach suggested by Hapfelmeier and Ulm (2013). This was done based on models comprising both croplands and grassland sites to draw general conclusions about management versus environmental factors. No relative importance measures were calculated at the land-use level since it is advised to run random-forest algorithms on datasets exceeding 100 samples (Ryo & Rillig, 2017).

We further explored the associations of the response variables with the selected predictors from the random forest models using partial dependence plots (R package *mlr* version 2.17.1; Bischl et al., 2016). This allowed us to investigate correlation patterns in the two land use types separately as well as to explore the characteristics of nonlinear associations (e.g., threshold-like behavior) of aggregate stability and SOC to the environmental and management factors. To support and illustrate the identified nonlinear relationships, the modelled associations and apparent thresholds were further explored using simple and segmented regression analyses. For simple regression analysis, the best fitting model was chosen testing linear, logarithmic, polynomial first-order, second-order, or third-order relationships between predictors and response variables. Additionally, segmented regression was conducted using the R package *segmented*, version 1.2.0 (Muggeo, 2008) to statistically test the thresholds observed through the partial dependence analysis and to estimate their confidence intervals. Since these parametric methods require a normal distribution of residuals, the MWD was log-transformed and SOC was square-root transformed.

2.6.4 | Exploring context dependency of management effects

Finally, we explored interactions between predictors, to evaluate which environmental factors determine the effect of land use and most important crop management practices, respectively, on soil aggregate stability and SOC stocks (e.g., to assess whether there is an effect of crop management in certain environmental conditions). This was done using a model-based tree algorithm, which couples the features of parametric statistical models such as linear models with decision tree models. With means of a linear model-based tree algorithm based on the M-fluctuation test (Zeileis et al., 2008), we searched for those predictors (from the pool of significant pedo-climatic predictors selected through the random forest algorithm) that significantly modulate the parameter values of the specified models assuming a linear relationship between land use/crop management and the response variables. The model-based tree algorithm was conducted using the package *partykit*, version 1.2.9 (Hothorn et al., 2015).

3 | RESULTS

3.1 | Land-use impact on soil aggregation and soil organic carbon across the European gradient

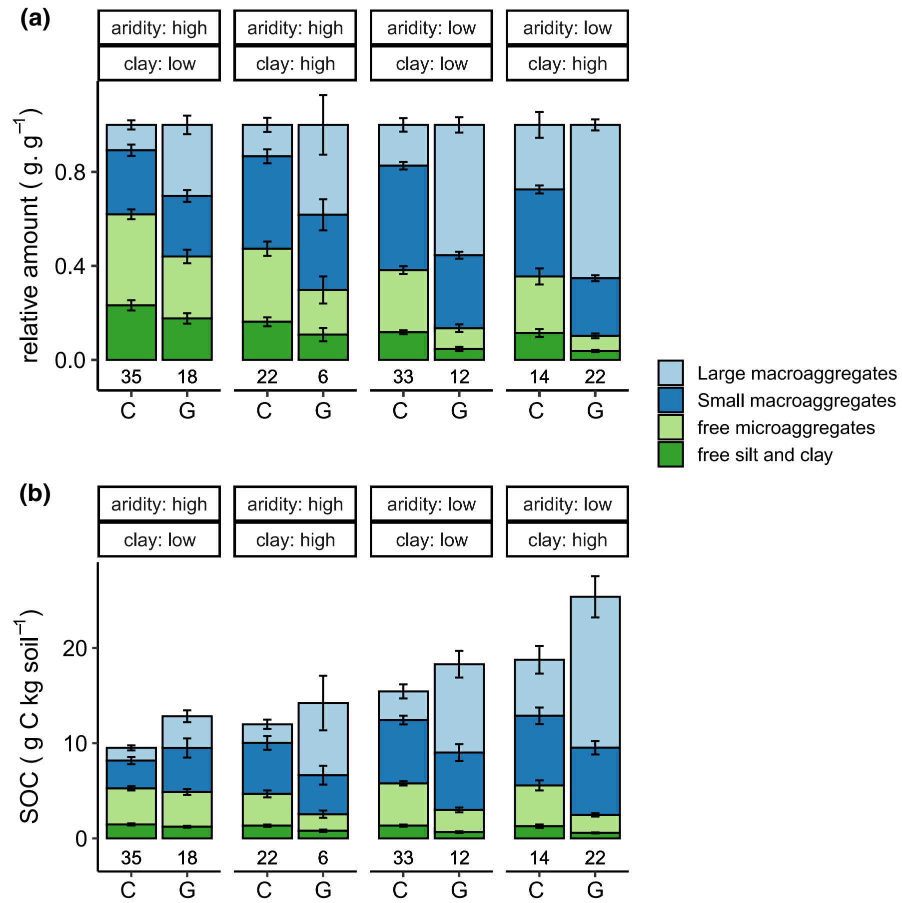
We observed an average MWD of soil aggregates of 1.25 mm in the cropland sites, and over twice this value in the neighboring uncropped grassland sites (2.83 mm; $p < .001$, Table S3), comprising extensively used grassland and marginal land. Similarly, SOC stocks at a depth of 20 cm were on average 1.5 times higher in uncropped grassland sites (28.5 Mg ha^{-1}) than in croplands (18.6 Mg ha^{-1}; Table S3). The distribution of SOC content associated with the different aggregate fractions varied amongst land use types across the studied sites (Figure 2b). Grouping sites into "high aridity" and "low aridity" as well as "high clay" and "low clay" sites, revealed that the MWD and SOC associated with aggregates decrease with higher aridity and increase with higher clay content. The absolute differences in macroaggregate-associated SOC pools were thus particularly pronounced in sites characterized by low aridity and high clay contents.

Regression analysis revealed a high correlation between SOC stocks and the MWD, which differed between croplands and grassland sites and was mediated by aridity (Figure 3). There was a strong linear relationship between MWD and SOC stocks in croplands. In grasslands, the relationship between MWD and SOC stocks levelled off at high SOC stock values, which were predominantly found in low aridity settings.

3.2 | Environmental drivers of aggregate stability and soil organic carbon across Europe

Using random forest analysis, we assessed the relative importance of land use and a range of climatic, edaphic, and crop management factors for explaining variations in soil aggregate stability and SOC stocks (Figure 4). Among 14 possible predictors, 13 significantly explained the variation in the MWD ($R^2 = 0.84$; Figure 4a). Land use had

FIGURE 2 The distribution of soil aggregate fractions (a) and soil organic carbon stored in aggregate fractions (b) in different land use systems (C-cropland; G-uncropped grassland). For visualization purposes, values were grouped into "high" and "low" aridity (high >0.12), and clay content (high >26.81%), respectively, using Jenks' natural breaks approach. Bar heights and error bars represent means ± standard error. Numbers below the bars refer to the number of observations for the respective group.



by far the strongest influence (R^2 =0.33), followed by the climatic gradient represented by aridity (R^2 =0.20) and MAT (R^2 =0.07). Even though the relative importance of management practices within croplands was small compared with climate and land use, a range of crop management predictors contributed significantly to explaining the variation of the MWD (9%) including crop cover and crop diversity (Figure 4b).

A similar set of predictors (n = 9) contributed to explaining a substantial amount of variation in SOC stocks (R^2 =0.69, Figure 4a). In contrast to soil aggregation, SOC stocks were shaped to a larger extent by soil properties (41%) and climate (39%; Figure 4b). Particularly soil Ca had a strong influence (R^2 =0.20) on variation in SOC, followed by aridity (R^2 =0.15) and MAT (0.10). Land use (7%) and crop management (2%) were significant predictors of SOC stocks but comparably less important than the MWD.

Using partial dependence plots, we further investigated the influence of the identified predictors in shaping MWD and C stocks in croplands and grassland sites separately (Figures S5 and S6). This analysis indicated that the importance of certain predictors differed between the two land use types. For example, soil Ca contents correlated more strongly with SOC stocks in grassland than in croplands (Figure S6a,b). In croplands, on the other hand, aridity and MAT correlated more strongly with SOC stocks than in grasslands.

3.3 | Nonlinear patterns of aggregate stability and SOC

Partial dependence plots also indicated nonlinear relationships of aridity and MAT with aggregate stability and SOC (Figures S5 and S6). These patterns were further investigated by simple and segmented regression analysis. Generally, the MWD decreased with increasing aridity and MAT (Figure 5a; Figure S7a). Additionally, we observed that the relationship between the MWD and MAT changed at a threshold ranging between 8.0 and 10.3°C. The relationship between aridity and MWD differed between land-use types. In uncropped grassland sites, the relationship between MWD and aridity levelled off at a threshold of 0.2 (0–0.4 confidence interval). This threshold was similar in arable sites (0.2–0.4), and an additional threshold was observed at about −0.1 (confidence interval − 0.2 – 0; Figure 5a). Importantly, this threshold-like behavior was consistently detected in the partial dependence plots (Figures S5 and S6) as well as the fitted second and third-order polynomial regressions, suggesting that the identified patterns were not sensitive to the selection of statistical models.

Total SOC exhibited similar trends compared with aggregate stability in the partial dependence plots (Figure 5b) where nonlinear patterns for aridity and MAT were visible. However, observed thresholds could only be confirmed for the aridity-SOC relationship, while the MAT–SOC relationship was fitted by a linear function with no breakpoints (Figure S7b). In addition to climate, we observed that SOC stocks increased drastically with increasing soil Ca content within a range of 10%–20%, especially in the uncropped grassland sites (Figure S6a). However, the uneven distribution of Ca content across the climatic gradient limited our ability to investigate Ca-mediated state changes using regression analysis.

Thresholds of aggregate stability and SOC along aridity and MAT gradients were further confirmed by a model-based tree, in the sense that these thresholds modulated the effect of land use on the MWD of soil aggregates and SOC stocks (Table S4). For example, the absolute difference in MWD was highest at an intermediate aridity between −1.32 and 0.48 (2.39 mm), and lowest under the most humid conditions (1.72 mm; Table S4a), corresponding to visual observations (Figure 5a). Notably, the relative difference in soil aggregate stability increased along with aridity, showing 0.8-fold (aridity <0.48), 2.05-fold (aridity −1.32–0.48) and 4.7-fold (aridity >0.48) increases in the MWD. Absolute differences in SOC stocks were driven by aridity, Ca content and temperature seasonality, spanning between 0.15 and 0.92 Mg ha^{-1} (Table S4b).

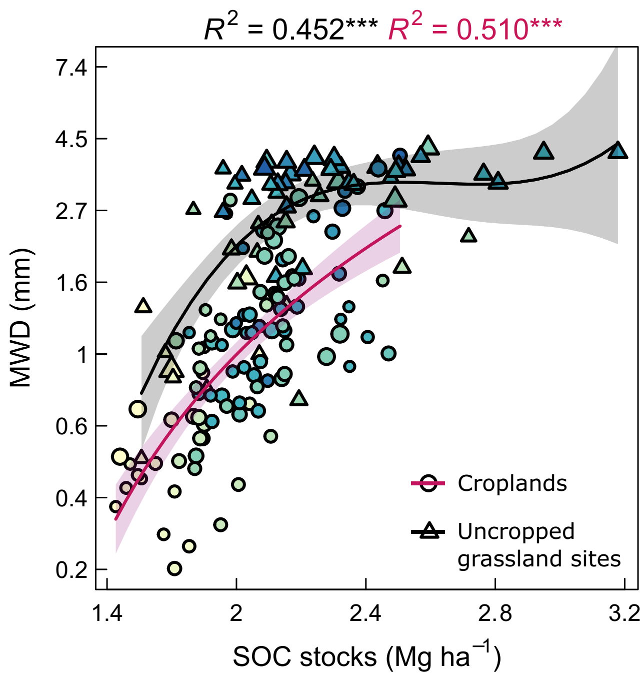


FIGURE 3 Relationships of the mean weight diameter (MWD) of soil aggregates (scale log-transformed) (a) and soil organic carbon stocks (scale sqrt-transformed) in croplands (pink lines) and uncropped grassland sites (black lines). Symbol sizes are proportional to soil clay contents, and symbol color corresponds to the aridity gradient across Europe (Figure 1). Solid lines show the best-fit polynomial regression models with the 0.95 confidence interval; respective R^2 values are shown at the top. Statistical significances are indicated as ***p < .001.

3.4 | Interaction effects of environmental and crop management variables on MWD and SOC

The prevailing influence of the climatic gradient, as well as Ca content, was consistently visible in the model-based tree analysis, which tests all possible interactions between the most important crop management practices and all other predictors (i.e., climatic, edaphic, and other management predictors) and suggests key interactions. Focusing on cropland sites, the algorithm revealed that the above-mentioned thresholds of aridity and soil Ca significantly modulated the relationship of crop management practices with the MWD of soil aggregates and SOC (Figure 6; Table S5).

We explored what drives the relationship between soil aggregate stability and crop diversity or crop cover (both showing a positive correlation in the partial dependence analysis, Figure S5b). When aridity levels were lower than 0.48, we observed that the

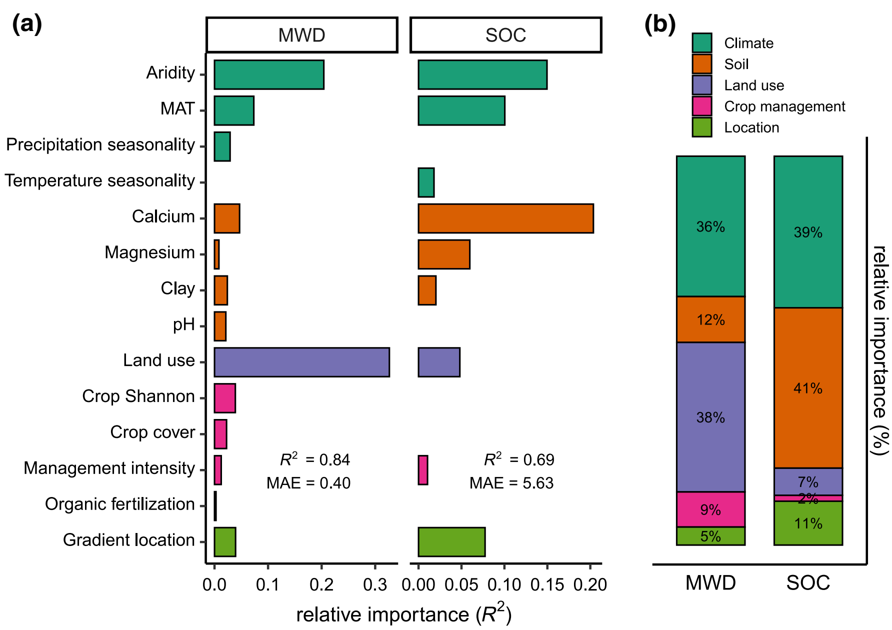


FIGURE 4 Predictor contribution to explaining the variation in the mean weight diameter (MWD) of soil aggregates and soil organic carbon stocks using random forests with variable selection (a). The fitted model performance is shown as R^2 and mean absolute error in the panels. The predictor contributions were grouped by climate, land use, soil characteristics, crop management practices, and the geographic location. The summed relative importance of each predictor group is visualized (b). Climate, land use, soil and location-related predictors applied to all sites (n = 162), while the crop management predictors were present only in arable sites (n = 104).

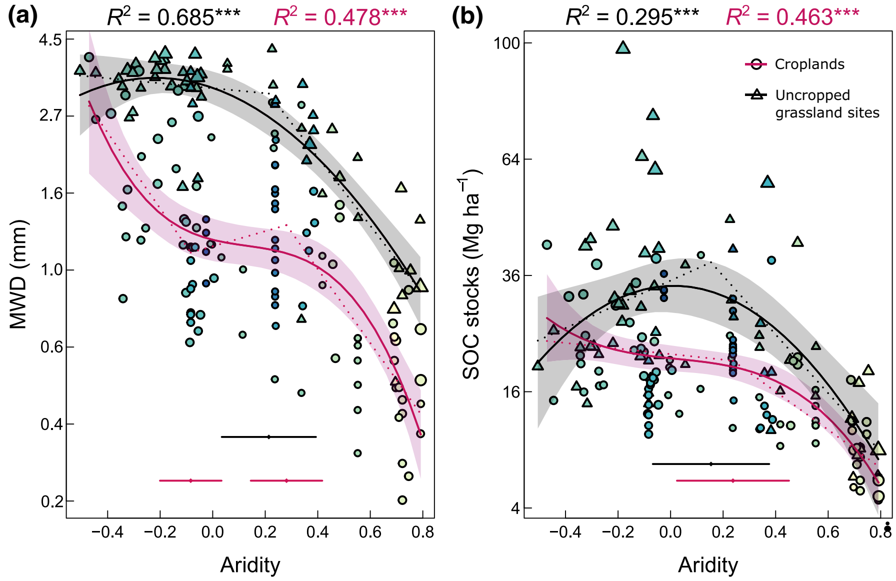


FIGURE 5 Relationships of the mean weight diameter of soil aggregates (scale log-transformed) (a) and soil organic carbon stocks (scale sqrt-transformed) (b) with aridity (1-aridity index, unitless). Symbol sizes are proportional to soil clay contents, and symbol color corresponds to the aridity gradient across Europe (Figure 1). Solid lines show the best-fit polynomial regression models with the 0.95 confidence interval; respective R^2 values are shown at the top. Statistical significances are indicated as $^{***}p < .001$. Dashed lines show segmented relationships with estimated breakpoints and respective 0.95 confidence intervals at the bottom of the plots.

MWD increased with crop diversity, particularly above a Shannon index of 1, while no such relationship was found at higher aridity levels. Focusing on SOC stocks, we observed a negative correlation with management intensity (Figure S6b), but only at aridity levels lower than 0.48 (Figure 6b). Interestingly, under this low aridity level, Ca values determined the strength of the observed management intensity–SOC relationship ($R^2 = 0.33$ where Ca ≤10.2; otherwise $R^2 = 0.12$), and SOC stocks tented to be higher in soils with high Ca content.

4 | DISCUSSION

In this large-scale, field-based study, we assessed the relative importance of land use, crop management, climatic conditions, and soil properties on soil aggregation and SOC storage. Our findings demonstrate higher soil aggregate stability (showing a 125% increase in MWD of soil aggregates) and SOC stocks (+53%) in the uncropped grassland sites compared with croplands. We found aridity thresholds determining SOC and aggregate stability, and most importantly, we provide evidence that such nonlinear patterns mediate the impacts of soil management (i.e., land use and cropping practices) on these variables. Here we discuss these findings in more detail, as well as the resulting potential to improve soil structure and SOC storage across the European gradient studied.

4.1 | Drivers and nonlinear patterns of aggregate stability and SOC across a European climatic and soil gradient

Climate and inherent soil properties were key drivers of soil aggregate stability and SOC storage, which is in line with previous studies (Bronick & Lal, 2005; Doetterl et al., 2015; Wiesmeier et al., 2019). Aridity was the most important climatic predictor for aggregate stability and SOC stocks. It is not surprising that aridity plays such a big role in soil structure and SOC, since changes in moisture levels can affect aggregation and SOC stabilization directly and indirectly through a number of mechanisms. First, aridity represents moisture availability for potential plant growth and biological activity and thus determines the amount of potential inputs of organic residues into the soil (Trabucco & Zomer, 2019). Higher inputs of plant residues, particularly of roots, enhance SOC storage (Kätterer et al., 2011) and increase microbial activity in the soil, stimulating aggregate formation and stabilization of SOC within aggregates (Watts et al., 2006). Apart from this, aridity may constrain the physical stabilization of aggregates through roots, and also the abundance and activity of microbes (Maestre et al., 2015; Manzoni et al., 2012; Querejeta et al., 2021), including fungal biomass and hyphal density (Wan et al., 2021; Weber et al., 2019), which play an important role for soil structure (Lehmann et al., 2017). Our results support these earlier observations, as we found more stable soil aggregates and a much bigger share of SOC protected within soil aggregates in soils stemming from sites with a lower aridity. Apart from this, MAT was particularly important for SOC stocks in our study. On the one hand, this could relate to the influence of MAT on potential evapotranspiration, in turn driving aridity. On the other hand, temperature exerts a strong control over decomposition rates of SOM (Davidson & Janssens, 2006; Ofiti et al., 2021), and lower MATs result in higher accumulation of SOC, at least when vegetation growth is not constrained by other factors like precipitation (Franzluebbers et al., 2001).

Evidence is growing that climate, and especially aridity, affects soil ecosystems in a nonlinear way (Feng et al., 2022). For example, Berdugo et al. (2020) showed that the response of multiple ecosystem attributes (including SOC) to increases in aridity follows a series of sequential thresholds in global drylands. Similarly, Bernardino et al. (2020) identified so-called turning points in ecosystem functioning of arid and semi-arid areas, and Pariente (2003) found an indication for a threshold-like behavior of soil structure linked to

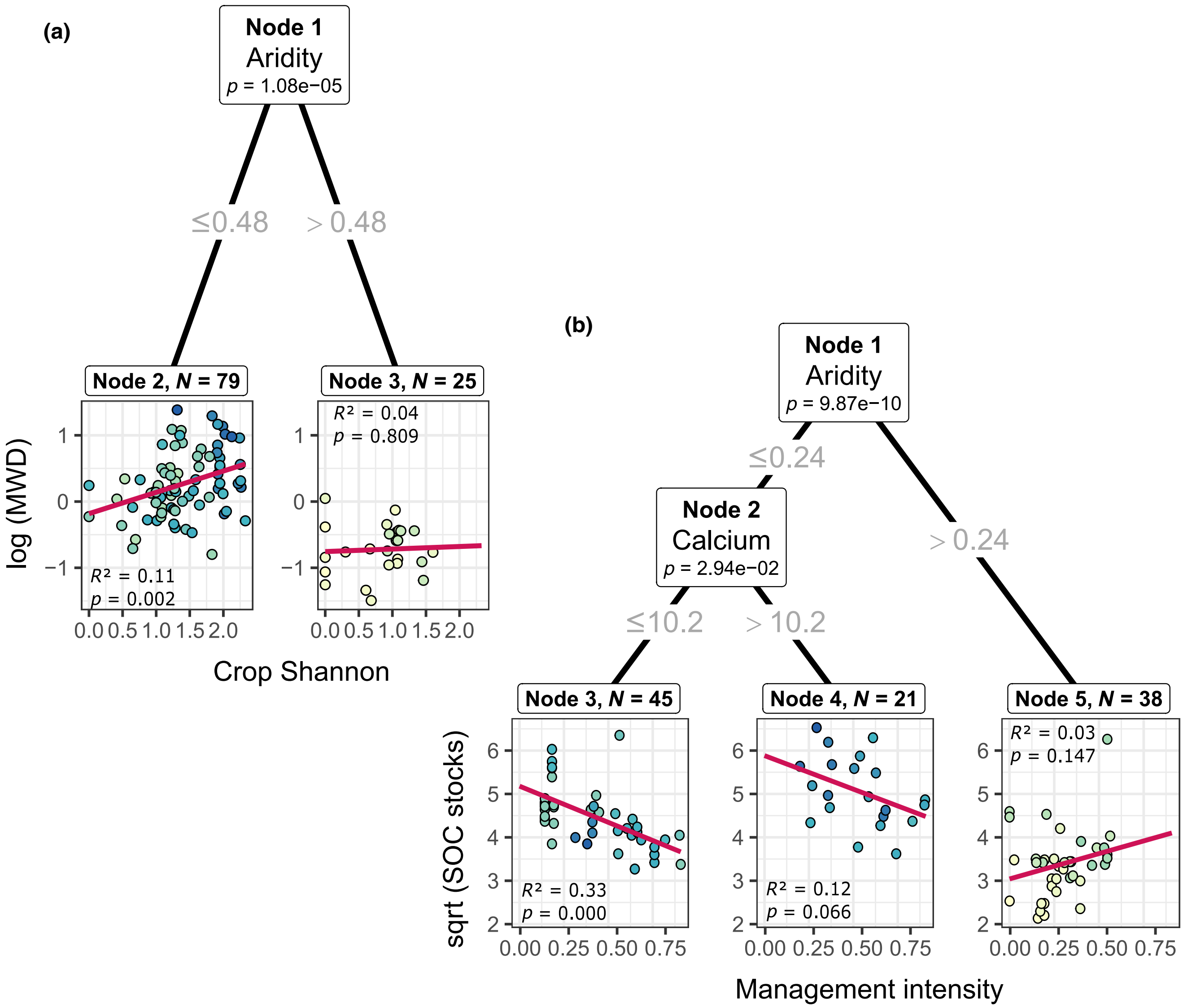


FIGURE 6 Drivers modulating the relationships between the mean weight diameter of soil aggregates (mm) and crop diversity (a); and drivers modulating the relationship between soil organic carbon stocks ($Mg\,ha^{-1}$) and management intensity (b). A linear model-based tree was used to detect environmental factors that have an interaction with the predictors in hierarchical order (i.e., split nodes). The resulting subsets (i.e., terminal nodes) show the context-dependent relationship modulated by the factors in the split nodes. Aridity (1–aridity index, unitless), soil calcium content ($cmol\,kg^{-1}$), *n* (number of observations).

aridity along a Mediterranean transect. In accordance with these previous studies, our results supported by multiple statistical models consistently suggest a nonlinear response of soil aggregate stability and SOC storage to increasing aridity levels. Thus, threshold-like responses to aridity may not only be valid for arid and semi-arid ecosystems but are also true for European agricultural land. Notably, the design of our study with a limited spatial coverage of data-points does not allow for pinpointing exact critical thresholds of aridity (which is highlighted by the wide confidence intervals of the estimated thresholds). However, the presented results underpin the validity of the ecosystem-threshold concept and provide an approximation of potential aridity thresholds ranging between 0 and 0.4 in European cropland and uncropped grassland sites. Interestingly, when converting the observed threshold values to AI values, they coincide with the AI of 0.65 (equaling aridity values of 0.35), which the UNEP World Atlas of Desertification (Jackson et al., 2017; Köchy et al., 2015) defined as the limit between drylands and nondrylands (Middleton & Thomas, 1997). Additionally, our results suggest the existence of another threshold at an aridity of −0.1, below which soil aggregate stability in arable fields increases and approaches the values of the uncropped grassland sites (Figure 5a). Similarly, the correlation between SOC stocks and MWD levelled off in sites with low aridity (Figure 3). This indicates a disconnection between aggregate stability and SOC storage in grasslands under humid conditions, which could have implications for aggregate-mediated SOC stabilization (Six, Conant, et al., 2002). It is important to note, however, that the observed saturation curve is distinct to the uncropped grassland sites studied, and may shift under different land use scenarios. Apart from this, the relationship between soil aggregate stability and SOC stocks depends on the method used to estimate aggregate stability (Haynes, 2000). In this study, we estimated the ability of soil aggregates to withstand disruptive forces such as slaking due to rewetting of dry soil. Slaking is an important breakdown mechanism for soil aggregates, especially in regions that experience periods of drought and heavy rainfall events, which is increasingly the case in many European countries (Rakovec et al., 2022; Zeder & Fischer, 2020). Mechanistic studies under different climate scenarios with respect to their distinct influences on soil aggregate stability and SOC accrual (e.g., taking slaking effects into account or not) are needed to provide further experimental evidence for the existence of thresholds of aggregate stability and SOC storage in response to aridity.

In addition to climate, we found that soil properties played a crucial role in SOC storage, even overshadowing the influence of MAT and aridity. It is well known that clay content plays an important role in the stabilization of soil organic matter and hence SOC storage (Hassink, 1997; Kaiser & Guggenberger, 2003), which is in line with our findings. For example, we found that fields with higher clay contents had higher levels of water-stable aggregates and more SOC stored within soil aggregates. However, in accordance with (Rasmussen et al., 2018) we show that exchangeable soil Ca is a much better predictor of SOC stocks than clay content, emphasizing the need to better reflect the role of various soil physicochemical properties for SOC in biogeochemical models. Based on current evidence, Ca can stabilize SOC through increased soil aggregation and chemical sorption, and it has widely been recognized that exchangeable Ca positively correlates with SOC (Bertrand et al., 2007; Rowley et al., 2018). Here we could not only further support the importance of Ca for SOC stabilization, but our results indicate that soil Ca contents might even modulate the response of SOC to soil management (Figure 6b). However, since the coverage of high and low Ca contents was not distributed homogenously across the climatic gradient studied, the observed interaction effects of Ca content and management on SOC stocks need to be further validated within controlled experimental settings in future studies.

4.2 | Sensitivity of soil aggregate stability and SOC to crop management under different environmental contexts

In our study, land use was the most important predictor of soil aggregate stability, yielding a relative importance of 38%. We ascribe the higher aggregate stability in the uncropped grassland sites to the omission of physical disturbance by ploughing and the permanent plant cover, allowing for a natural build-up of soil structure (Or et al., 2021), for example, through the stabilization of soil particles by roots and hyphae (Barto et al., 2010). For SOC stocks, land use contributed to only 7% of the explained variation, due to the overruling importance of edaphic and climatic conditions (Figure 4). This is in support of previous studies showing that the direction and magnitude of the shifts in SOC after conversion to cropland depend on climate factors and soil mineralogy (Powers et al., 2011). Similarly, we found that pedo-climatic conditions (climate and soil Ca content) determined the magnitude of differences in aggregate stability and SOC between the two land-use types, with largest differences found in regions with intermediate to low aridity suggesting that arid conditions pose a limitation to soil aggregation and build-up of SOC (Plaza et al., 2018). It is important to keep in mind that this study specifically focused on wheat cropping systems and that the relative importance of land use on SOC will depend on the specific crops planted (Mathew et al., 2017).

Apart from land use differences, management practices used for crop cultivation are known to exert a strong influence on soil structure and SOC (Bronick & Lal, 2005; Liu et al., 2006; Wiesmeier et al., 2019). In this study, we detected beneficial effects of crop diversity for soil aggregation and SOC storage across a large spatial gradient, in line with earlier findings demonstrating the benefits of crop rotations compared with mono-cropping (Bai et al., 2018), and diversified crop rotations within specific locations (Tiemann et al., 2015). There may be several mechanisms explaining the positive influence of diverse cropping systems on soils. For example, the benefits of crop diversification (e.g., through the inclusion of cover crops) on soil ecosystems have been attributed to higher and more diverse inputs of fresh C to the soil, stimulating microbial abundance and activity (Poeplau & Don, 2015; Rosenzweig et al., 2018; Tiemann et al., 2015). Although this study suggests that a higher diversity of crops promotes SOC storage and aggregation, the inclusion of specific crops in the crop rotation, such as grass-clover leys, can be particularly beneficial for aggregate-mediated SOC accrual (Guest et al., 2022). Future studies exploring complex crop rotations should therefore also consider the identity of crops in the crop rotation, including associated management practices (e.g., hoeing in beets and pumpkin).

Crop management intensity (estimated by a composite index including tillage, fertilization, and pesticide use) was negatively linked to SOC and aggregate stability in this present study, which underpins the mounting evidence that management intensity can have adverse effects on soil ecosystems (Banerjee et al., 2019; Liu et al., 2006; Qin et al., 2017; Tsiafouli et al., 2015). Particularly soil fungal communities, which play an important role in soil aggregation (Lehmann et al., 2017; Morris et al., 2019) and have been linked to increased SOC (Beare et al., 1997; Six et al., 2006; Wilson et al., 2009), are often negatively impacted by intensive management practices such as tillage (Beare et al., 1997), fertilization (Treseder, 2004) and pesticide use (Edlinger et al., 2022; Hage-Ahmed et al., 2019; Riedo et al., 2021). The growing evidence of the deteriorating effects of intensive agricultural management on soils calls for finding ways to maintain crop yield while avoiding negative impacts on soil ecosystems, especially if soils should serve as a natural climate solution (Bossio et al., 2020; Paustian et al., 2016). For example, organic fertilization can enhance soil aggregation (Abiven et al., 2009), and we also observed indications of this positive connection in this study (Figure 4a). Considering also the quantity, type and quality of the organic fertilizer may hence provide a better picture of the relative importance of organic fertilization on SOC storage in future studies.

Our results suggest that the sensitivity of SOC and aggregate stability to management practices is strongly regulated by pedoclimatic conditions (Figure 6). For instance, SOC stocks and soil aggregation appeared to be particularly sensitive to differences in management intensity, crop diversity and crop cover in less-arid contexts (aridity <0.48), while no significant relationship was found under dryland conditions (aridity >0.48). In this study, we found a higher proportion of silt and clay associated SOC with increasing aridity values (Figure 2), thus likely contributing to the lower impact of management practices on this carbon pool. In less arid conditions, on the other hand, the potential for a build-up of SOM through physical protection in soil macro-aggregates appeared to be higher. Macro-aggregate-mediated stabilization of SOM has been identified as a major pathway for the build-up of SOC (Guest et al., 2022; Six et al., 2000). However, macroaggregates and their associated SOC such as particulate organic carbon are also highly susceptible to management (Six et al., 2000) and other factors of global change (Rocci et al., 2021). Therefore, we conclude that in European nondryland regions, where the climatic potential for C storage as well as the susceptibility for SOC losses appear to be largest, the protection and aggregate-mediated build-up of SOC through appropriate soil management is crucial regarding climate change mitigation goals.

5 | CONCLUSION

In this study, we assessed the relative importance and interactions of climatic factors, soil properties, and management practices on soil aggregate stability and SOC storage across European agricultural soils. We found that soil properties and climate strongly regulate SOC storage and structure and that these soil properties respond to gradients in aridity and temperature in a nonlinear way. Most importantly, we provide evidence that the observed threshold-like behavior of soil aggregate stability and SOC stocks influences the impacts of soil management (i.e., land use and cropping practices) on these variables. While care should be taken in the interpretation and extrapolation of proposed aridity thresholds to other ecosystems or regions, this study highlights that agricultural management goals and practices should be tailored to the biogeographic context to make use of the potential of soils to serve as C sinks and, thus, to fulfill their potential to mitigate ongoing climate change.

ACKNOWLEDGMENTS

We are thankful to all the farmers and farm managers for allowing us to sample their fields and for completing our detailed questionnaires. We also thank Alain Held, Andrea Bonvicini, Susanne Müller, Shuai Zhao, Vincent Somerville, Andri Brugger, Orlando Scholz, David Bugmann, Robin Heiz, Benjamin Seitz, and Miriam Roser from the Plant–Soil Interactions Group at Agroscope for help with both field work and lab analyses. The Digging Deeper project was funded through the 2015–2016 BiodivERsA COFUND call for research proposals, with the national funders Swiss National Science Foundation (grant 31BD30-172462), Deutsche Forschungsgemeinschaft (317895346), Swedish Research Council Formas (contract 2016-0194), Ministerio de Economía y Competitividad (Digging_Deeper, Ref. PCIN-2016-028) and Agence Nationale de la Recherche (ANR, France; grant ANR-16-EBI3-0004-01). Open access funding provided by Agroscope.

CONFLICT OF INTEREST STATEMENT

The authors declare no competing interests.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available in "figshare" at 10.6084/m9.figshare.19762114.

ORCID

Anna Edlinger https://orcid.org/0000-0003-3538-2371
Gina Garland https://orcid.org/0000-0002-1657-3669
Samiran Banerjee https://orcid.org/0000-0002-1402-0171
Florine Degrune https://orcid.org/0000-0002-3409-5859
Pablo García-Palacios https://orcid.org/0000-0002-6367-4761
Chantal Herzog https://orcid.org/0000-0002-3085-2015
David Sánchez Pescador https://orcid.org/0000-0003-0395-9543
Masahiro Ryo https://orcid.org/0000-0002-5271-3446
Aurélien Saghaï https://orcid.org/0000-0002-7069-2159
Sara Hallin https://orcid.org/0000-0002-9069-9024
Fernando T. Maestre https://orcid.org/0000-0002-7434-4856
Laurent Philippot https://orcid.org/0000-0003-3461-4492
Matthias C. Rillig https://orcid.org/0000-0003-3541-7853
Marcel G. A. van der Heijden https://orcid.org/0000-0001-7040-1924

REFERENCES

Abiven, S., Menasseri, S., & Chenu, C. (2009). The effects of organic inputs over time on soil aggregate stability—A literature analysis. *Soil Biology and Biochemistry*, *41*(1), 1–12. https://doi.org/10.1016/j.soilbio.2008.09.015

Bai, Z., Caspari, T., Gonzalez, M. R., Batjes, N. H., Mäder, P., Bünemann, E. K., de Goede, R., Brussaard, L., Xu, M., Ferreira, C. S. S., Reintam, E., Fan, H., Mihelič, R., Glavan, M., & Tóth, Z. (2018). Effects of agricultural management practices on soil quality: A review of long-term experiments for Europe and China. *Agriculture, Ecosystems & Environment*, *265*, 1–7. https://doi.org/10.1016/J.AGEE.2018.05.028

Banerjee, S., Walder, F., Büchi, L., Meyer, M., Held, A. Y., Gattinger, A., Keller, T., Charles, R., & van der Heijden, M. G. A. (2019). Agricultural intensification reduces microbial network complexity and the abundance of keystone taxa in roots. *ISME Journal*, *13*(7), 1722–1736. https://doi.org/10.1038/s41396-019-0383-2

Barto, E. K., Alt, F., Oelmann, Y., Wilcke, W., & Rillig, M. C. (2010). Contributions of biotic and abiotic factors to soil aggregation across a land use gradient. *Soil Biology and Biochemistry*, *42*(12), 2316–2324. https://doi.org/10.1016/j.soilbio.2010.09.008

Beare, M. H., Hu, S., Coleman, D. C., & Hendrix, P. F. (1997). Influences of mycelial fungi on soil aggregation and organic matter storage in conventional and no-tillage soils. *Applied Soil Ecology*, *5*, 211–219. https://doi.org/10.1016/S0929-1393(96)00142-4

Berdugo, M., Delgado-Baquerizo, M., Soliveres, S., Hernández-Clemente, R., Zhao, Y., Gaitán, J. J., Gross, N., Saiz, H., Maire, V., Lehman, A., Rillig, M. C., Solé, R. V., & Maestre, F. T. (2020). Global ecosystem thresholds driven by aridity. *Science*, *367*(6479), 787–790. https://doi.org/10.1126/science.aay5958

Bernardino, P. N., de Keersmaecker, W., Fensholt, R., Verbesselt, J., Somers, B., & Horion, S. (2020). Global-scale characterization of turning points in arid and semi-arid ecosystem functioning. *Global Ecology and Biogeography*, *29*(7), 1230–1245. https://doi.org/10.1111/geb.13099

Bertrand, I., Delfosse, O., & Mary, B. (2007). Carbon and nitrogen mineralization in acidic, limed and calcareous agricultural soils: Apparent and actual effects. *Soil Biology & Biochemistry*, *39*, 276–288. https://doi.org/10.1016/j.soilbio.2006.07.016

Bischl, B., Lang, M., Kotthoff, L., Schiffner, J., Richter, J., Studerus, E., Casalicchio, G., & Jones, Z. M. (2016). Mlr: Machine learning in R. *Journal of Machine Learning Research*, *17*(170), 1–5.

Bossio, D. A., Cook-Patton, S. C., Ellis, P. W., Fargione, J., Sanderman, J., Smith, P., Wood, S., Zomer, R. J., von Unger, M., Emmer, I. M., & Griscom, B. W. (2020). The role of soil carbon in natural climate solutions. *Nature Sustainability*, *3*(5), 391–398. https://doi.org/10.1038/s41893-020-0491-z

Breiman, L. (2001). Random forests. *Machine Learning*, *45*(1), 5–32. https://doi.org/10.1023/A:1010933404324

Bronick, C. J., & Lal, R. (2005). Soil structure and management: A review. *Geoderma*, *124*(1–2), 3–22. https://doi.org/10.1016/j.geoderma.2004.03.005

Bünemann, E. K., Bongiorno, G., Bai, Z., Creamer, R. E., De Deyn, G., de Goede, R., Fleskens, L., Geissen, V., Kuyper, T. W., Mäder, P., Pulleman, M., Sukkel, W., van Groenigen, J. W., & Brussaard, L. (2018). Soil quality—A critical review. In *Soil biology and biochemistry* (Vol. *120*, pp. 105–125). Pergamon. https://doi.org/10.1016/j.soilbio.2018.01.030

Chenu, C., Angers, D. A., Barré, P., Derrien, D., Arrouays, D., & Balesdent, J. (2019). Increasing organic stocks in agricultural soils: Knowledge gaps and potential innovations. *Soil and Tillage Research*, *188*, 41–52. https://doi.org/10.1016/j.still.2018.04.011

Corti, G., Ugolini, F. C., & Agnelli, A. (1998). Classing the soil skeleton (greater than two millimeters): Proposed approach and procedure. *Soil Science Society of America Journal*, *62*(6), 1620–1629. https://doi.org/10.2136/sssaj1998.03615995006200060020x

Crowther, T. W., Todd-Brown, K. E. O., Rowe, C. W., Wieder, W. R., Carey, J. C., MacHmuller, M. B., Snoek, B. L., Fang, S., Zhou, G., Allison, S. D., Blair, J. M., Bridgham, S. D., Burton, A. J., Carrillo, Y., Reich, P. B., Clark, J. S., Classen, A. T., Dijkstra, F. A., Elberling, B., … Bradford, M. A. (2016). Quantifying global soil carbon losses in response to warming. *Nature*, *540*(7631), 104–108. https://doi.org/10.1038/nature20150

Davidson, E. A., & Janssens, I. A. (2006). Temperature sensitivity of soil carbon decomposition and feedbacks to climate change. *Nature*, *440*(7081), 165–173. https://doi.org/10.1038/nature04514

Delgado-Baquerizo, M., Maestre, F. T., Reich, P. B., Jeffries, T. C., Gaitan, J. J., Encinar, D., Berdugo, M., Campbell, C. D., & Singh, B. K. (2016). Microbial diversity drives multifunctionality in terrestrial ecosystems. *Nature Communications*, *7*(1), 10541. https://doi.org/10.1038/ncomms10541

Doetterl, S., Stevens, A., Six, J., Merckx, R., van Oost, K., Casanova Pinto, M., Casanova-Katny, A., Muñoz, C., Boudin, M., Zagal Venegas, E., & Boeckx, P. (2015). Soil carbon storage controlled by interactions between geochemistry and climate. *Nature Geoscience*, *8*(10), 780–783. https://doi.org/10.1038/ngeo2516

Edlinger, A., Garland, G., Banerjee, S., Degrune, F., García-Palacios, P., Herzog, C., Sánchez-Pescador, D., Romdhane, S., Ryo, M., Saghai, A., Hallin, S., Maestre, F. T., Philippot, L., Rillig, M., & van der Heijden, M. (2023). The impact of agricultural management on soil aggregation and carbon storage is regulated by climate. Digging Deeper Dataset. Figshare. https://doi.org/10.6084/m9.figshare.19762114

Edlinger, A., Garland, G., Hartman, K., Banerjee, S., Degrune, F., García-Palacios, P., Hallin, S., Valzano-Held, A., Herzog, C., Jansa, J., Kost, E., Maestre, F. T., Pescador, D. S., Philippot, L., Rillig, M. C., Romdhane, S., Saghaï, A., Spor, A., Frossard, E., & van der Heijden, M. G. A. (2022). Agricultural management and pesticide use reduce the functioning of beneficial plant symbionts. *Nature Ecology and Evolution*, *6*(8), 1145–1154. https://doi.org/10.1038/s41559-022-01799-8

Ellert, B. H., & Bettany, J. R. (1995). Calculation of organic matter and nutrients stored in soils under contrasting management regimes. *Canadian Journal of Soil Science*, *75*, 529–538.

Elliott, E. T. (1986). Aggregate structure and carbon, nitrogen, and phosphorus in native and cultivated soils. *Soil Science Society of America Journal*, *50*(3), 627–633.

Elliott, E. T. (2010). Aggregate structure and carbon, nitrogen, and phosphorus in native and cultivated soils. *Soil Science Society of America Journal*, *50*, 627–633. https://doi.org/10.2136/sssaj1986.03615995005000030017x

Eurostat. (2018). *LUCAS 2018 Technical reference document C3 Classification (Land cover & Land use)*. *2018*, 98. https://ec.europa.eu/eurostat/documents/205002/8072634/LUCAS2018-C3-Classification.pdf

Feng, Y., Zhang, J., Berdugo, M., Guirado, E., Guerra, C. A., Egidi, E., Wang, J., Singh, B. K., & Delgado-Baquerizo, M. (2022). Temperature thresholds drive the global distribution of soil fungal decomposers. *Global Change Biology*, *28*(8), 2779–2789. https://doi.org/10.1111/gcb.16096

Fick, S. E., & Hijmans, R. J. (2017). WorldClim 2: New 1-km spatial resolution climate surfaces for global land areas. *International Journal of Climatology*, *37*(12), 4302–4315. https://doi.org/10.1002/joc.5086

Foley, J. A., Ramankutty, N., Brauman, K. A., Cassidy, E. S., Gerber, J. S., Johnston, M., Mueller, N. D., O'Connell, C., Ray, D. K., West, P. C., Balzer, C., Bennett, E. M., Carpenter, S. R., Hill, J., Monfreda, C., Polasky, S., Rockström, J., Sheehan, J., Siebert, S., … Zaks, D. P. M. (2011). Solutions for a cultivated planet. *Nature*, *478*(7369), 337–342. https://doi.org/10.1038/nature10452

Franzluebbers, A. J., Haney, R. L., Honeycutt, C. W., Arshad, M. A., Schomberg, H. H., & Hons, F. M. (2001). Climatic influences on active fractions of soil organic matter. *Soil Biology and Biochemistry*, *33*(7–8), 1103–1111. https://doi.org/10.1016/S0038-0717(01)00016-5

García-Palacios, P., Gross, N., Gaitán, J., & Maestre, F. T. (2018). Climate mediates the biodiversity-ecosystem stability relationship globally. *Proceedings of the National Academy of Sciences of the United States of America*, *115*(33), 8400–8405. https://doi.org/10.1073/pnas.1800425115

Garland, G., Banerjee, S., Edlinger, A., Miranda Oliveira, E., Herzog, C., Wittwer, R., Philippot, L., Maestre, F. T., & van der Heijden, M. G. A. (2021). A closer look at the functions behind ecosystem multifunctionality: A review. *Journal of Ecology*, *109*(2), 600–613. https://doi.org/10.1111/1365-2745.13511

Guest, E. J., Palfreeman, L. J., Holden, J., Chapman, P. J., Firbank, L. G., Lappage, M. G., Helgason, T., & Leake, J. R. (2022). Soil macroaggregation drives sequestration of organic carbon and nitrogen with three-year grass-clover leys in arable rotations. *Science of the Total Environment*, *852*, 158358. https://doi.org/10.1016/j.scitotenv.2022.158358

Guo, L. B., & Gifford, R. M. (2002). Soil carbon stocks and land use change: A meta analysis. *Global Change Biology*, *8*(4), 345–360. https://doi.org/10.1046/j.1354-1013.2002.00486.x

Hage-Ahmed, K., Rosner, K., & Steinkellner, S. (2019). Arbuscular mycorrhizal fungi and their response to pesticides. *Pest Management Science*, *75*, 583–590. https://doi.org/10.1002/ps.5220

Hapfelmeier, A., & Ulm, K. (2013). A new variable selection approach using random forests. *Computational Statistics and Data Analysis*, *60*(1), 50–69. https://doi.org/10.1016/j.csda.2012.09.020

Hassink, J. (1997). A model of the physical protection of organic matter in soils the capacity of soils to preserve organic C and N by their association with clay and silt particles. *Plant and Soil*, *191*, 77–87. https://www.researchgate.net/publication/40154117

Haynes, R. J. (2000). Interactions between soil organic matter status, cropping history, method of quantification and sample pretreatment and their effects on measured aggregate stability. *Biology and Fertiity of Soils*, *30*, 270–275.

Hothorn, T., Zeileis, A., Cheng, E., & Ong, S. (2015). partykit: A modular toolkit for recursive Partytioning in R. *Journal of Machine Learning Research*, *16*(118), 3905–3909.

Jackson, R. B., Lajtha, K., Crow, S. E., Hugelius, G., Kramer, M. G., & Piñeiro, G. (2017). The ecology of soil carbon: Pools, vulnerabilities, and biotic and abiotic controls. *Annual Review of Ecology, Evolution, and Systematics*, *48*, 419–445. https://doi.org/10.1146/annurev-ecolsys-112414-054234

Jenks, G. F. (1967). *The data model concept in statistical mapping. International Yearbook of Cartography* (Vol. *7*, pp. 186–190). C. Vertelsmans Verlag.

Kaiser, K., & Guggenberger, G. (2003). Mineral surfaces and soil organic matter. *European Journal of Soil Science*, *54*(2), 219–236. https://doi.org/10.1046/j.1365-2389.2003.00544.x

Kätterer, T., Bolinder, M. A., Andrén, O., Kirchmann, H., & Menichetti, L. (2011). Roots contribute more to refractory soil organic matter than above-ground crop residues, as revealed by a long-term field experiment. *Agriculture, Ecosystems & Environment*, *141*(1–2), 184–192. https://doi.org/10.1016/j.agee.2011.02.029

Keel, S. G., Anken, T., Büchi, L., Chervet, A., Fliessbach, A., Flisch, R., Huguenin-Elie, O., Mäder, P., Mayer, J., Sinaj, S., Sturny, W., Wüst-Galley, C., Zihlmann, U., & Leifeld, J. (2019). Loss of soil organic carbon in Swiss long-term agricultural experiments over a wide range of management practices. *Agriculture, Ecosystems & Environment*, *286*, 106654. https://doi.org/10.1016/J.AGEE.2019.106654

Köchy, M., Hiederer, R., & Freibauer, A. (2015). Global distribution of soil organic carbon—Part 1: Masses and frequency distributions of SOC stocks for the tropics, permafrost regions, wetlands, and the world. *The Soil*, *1*(1), 351–365. https://doi.org/10.5194/soil-1-351-2015

Lal, R. (2004). Agricultural activities and the global carbon cycle. *Nutrient Cycling in Agroecosystems*, *70*(2), 103–116. https://doi.org/10.1023/B:FRES.0000048480.24274.0f

Lee, J., Hopmans, J. W., Rolston, D. E., Baer, S. G., & Six, J. (2009). Determining soil carbon stock changes: Simple bulk density corrections fail. *Agriculture, Ecosystems and Environment*, *134*(3–4), 251–256. https://doi.org/10.1016/j.agee.2009.07.006

Lehmann, A., Zheng, W., & Rillig, M. C. (2017). Soil biota contributions to soil aggregation. *Nature Ecology & Evolution*, *1*(12), 1828–1835. https://doi.org/10.1038/s41559-017-0344-y

Lehmann, J., Bossio, D. A., Kögel-Knabner, I., & Rillig, M. C. (2020). The concept and future prospects of soil health. *Nature Reviews Earth & Environment*, *1*(10), 544–553. https://doi.org/10.1038/s43017-020-0080-8

Liaw, A., & Wiener, M. (2002). Classification and regression by randomForest. *R News*, *2*(3), 18–22.

Liu, X., Herbert, S. J., Hashemi, A. M., Zhang, X., & Ding, G. (2006). Effects of agricultural management on soil organic matter and carbon transformation—A review. *Plant, Soil and Environment*, *52*(12), 531–543.

Mäder, P., Fliessbach, A., Dubois, D., Gunst, L., Fried, P., & Niggli, U. (2002). Soil fertility and biodiversity in organic farming. *Science*, *296*(5573), 1694–1697. https://doi.org/10.1126/science.1071148

Maestre, F. T., Delgado-Baquerizo, M., Jeffries, T. C., Eldridge, D. J., Ochoa, V., Gozalo, B., Quero, J. L., García-Gómez, M., Gallardo, A., Ulrich, W., Bowker, M. A., Arredondo, T., Barraza-Zepeda, C., Bran, D., Florentino, A., Gaitán, J., Gutiérrez, J. R., Huber-Sannwald, E., Jankju, M., … Singh, B. K. (2015). Increasing aridity reduces soil microbial diversity and abundance in global drylands. *Proceedings of the National Academy of Sciences of the United States of America*, *112*(51), 15684–15689. https://doi.org/10.1073/pnas.1516684112

Manzoni, S., Schimel, J. P., & Porporato, A. (2012). Responses of soil microbial communities to water stress: Results from a meta-analysis. *Ecology*, *93*(4), 930–938. https://doi.org/10.1890/11-0026.1

Mascaro, J., Asner, G. P., Knapp, D. E., Kennedy-Bowdoin, T., Martin, R. E., Anderson, C., Higgins, M., & Chadwick, K. D. (2014). A tale of two "forests": Random Forest machine learning Aids tropical Forest carbon mapping. https://doi.org/10.1371/journal.pone.0085993

Mathew, I., Shimelis, H., Mutema, M., & Chaplot, V. (2017). What crop type for atmospheric carbon sequestration: Results from a global data analysis. *Agriculture, Ecosystems and Environment*, *243*, 34–46. https://doi.org/10.1016/j.agee.2017.04.008

McDaniel, M. D., Tiemann, L. K., & Grandy, A. S. (2014). Does agricultural crop diversity enhance soil microbial biomass and organic matter dynamics? A meta-analysis. *Ecological Applications*, *24*(3), 560–570. https://doi.org/10.1890/13-0616.1

Middleton, N., & Thomas, D. (1997). *World atlas of desertification* (2nd ed.). Arnold, Hodder Headline, PLC.

Morris, E. K., Morris, D. J. P., Vogt, S., Gleber, S. C., Bigalke, M., Wilcke, W., & Rillig, M. C. (2019). Visualizing the dynamics of soil aggregation as affected by arbuscular mycorrhizal fungi. *ISME Journal*, *13*, 1639–1646. https://doi.org/10.1038/s41396-019-0369-0

Muggeo, V. R. (2008). Segmented: An R package to fit regression models with broken-line relationships. *R News*, *3*(6), 343–344. https://doi.org/10.1159/000323281

Ofiti, N. O. E., Zosso, C. U., Soong, J. L., Solly, E. F., Torn, M. S., Wiesenberg, G. L. B., & Schmidt, M. W. I. (2021). Warming promotes loss of subsoil carbon through accelerated degradation of plant-derived organic matter. *Soil Biology and Biochemistry*, *156*, 108185. https://doi.org/10.1016/j.soilbio.2021.108185

Or, D., Keller, T., & Schlesinger, W. H. (2021). Natural and managed soil structure: On the fragile scaffolding for soil functioning. *Soil and Tillage Research*, *208*(2020), 104912. https://doi.org/10.1016/j.still.2020.104912

Pariente, S. (2003). Nonlinearity of ecogeomorphic processes along mediterranean-arid transect. https://doi.org/10.1016/j.geomorph.2003.09.019

Paustian, K., Lehmann, J., Ogle, S., Reay, D., Robertson, G. P., Smith, P., & Kellogg, W. K. (2016). "Climate-smart" soils: A new management paradigm for global agriculture. *Nature*, *532*, 49–57. https://doi.org/10.1038/nature17174

Plaza, C., Zaccone, C., Sawicka, K., Méndez, A. M., Tarquis, A., Gascó, G., Heuvelink, G. B. M., Schuur, E. A. G., & Maestre, F. T. (2018). Soil resources and element stocks in drylands to face global issues. *Scientific Reports*, *8*(1), 13788. https://doi.org/10.1038/s41598-018-32229-0

Poeplau, C., & Don, A. (2015). Carbon sequestration in agricultural soils via cultivation of cover crops—A meta-analysis. *Agriculture, Ecosystems and Environment*, *200*, 33–41. https://doi.org/10.1016/j.agee.2014.10.024

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. *The Soil*, *3*(1), 61–66. https://doi.org/10.5194/soil-3-61-2017

Powers, J. S., Corre, M. D., Twine, T. E., & Veldkamp, E. (2011). Geographic bias of field observations of soil carbon stocks with tropical land-use changes precludes spatial extrapolation. *Proceedings of the National Academy of Sciences of the United States of America*, *108*(15), 6318–6322. https://doi.org/10.1073/pnas.1016774108

Qin, H., Chen, J., Wu, Q., Niu, L., Li, Y., Liang, C., Shen, Y., & Xu, Q. (2017). Intensive management decreases soil aggregation and changes the abundance and community compositions of arbuscular mycorrhizal fungi in Moso bamboo (*Phyllostachys pubescens*) forests. *Forest Ecology and Management*, *400*, 246–255. https://doi.org/10.1016/j.foreco.2017.06.003

Querejeta, J. I., Schlaeppi, K., López-García, Á., Ondoño, S., Prieto, I., van der Heijden, M. G. A., & Mar Alguacil, M. (2021). Lower relative abundance of ectomycorrhizal fungi under a warmer and drier climate is linked to enhanced soil organic matter decomposition. *New Phytologist*, *232*(3), 1399–1413. https://doi.org/10.1111/nph.17661

R Core Team. (2018). *R: A language and environment for statistical computing*. Version 3.5. 2. R Foundation for Statistical Computing.

Rabosky, D., Grundler, M., Anderson, C., Title, P., Shi, J., Brown, J., Huang, H., & Larson, J. (2014). BAMMtools: An R package for the analysis of evolutionary dynamics on phylogenetic trees. *Methods in Ecology and Evolution*, *5*, 701–707.

Rakovec, O., Samaniego, L., Hari, V., Markonis, Y., Moravec, V., Thober, S., Hanel, M., & Kumar, R. (2022). The 2018–2020 multi-year drought sets a new benchmark in Europe. *Earth's Futures*, *10*(3), 1–11. https://doi.org/10.1029/2021EF002394

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., & Wagai, R. (2018). Beyond clay: Towards an improved set of variables for predicting soil organic matter content. *Biogeochemistry*, *137*(3), 297–306. https://doi.org/10.1007/s10533-018-0424-3

Riedo, J., Wettstein, F. E., Rösch, A., Herzog, C., Banerjee, S., Büchi, L., Charles, R., Wächter, D., Martin-Laurent, F., Bucheli, T. D., Walder, F., & van der Heijden, M. G. A. (2021). Widespread occurrence of pesticides in organically managed agricultural soils—The ghost of a conventional agricultural past? *Environmental Science & Technology*, *55*, 2919–2928. https://doi.org/10.1021/acs.est.0c06405

Rocci, K. S., Lavallee, J. M., Stewart, C. E., & Cotrufo, M. F. (2021). Soil organic carbon response to global environmental change depends on its distribution between mineral-associated and particulate organic matter: A meta-analysis. *Science of the Total Environment*, *793*, 148569. https://doi.org/10.1016/j.scitotenv.2021.148569

Rosenzweig, S. T., Fonte, S. J., & Schipanski, M. E. (2018). Intensifying rotations increases soil carbon, fungi, and aggregation in semi-arid agroecosystems. *Agriculture, Ecosystems & Environment*, *258*, 14–22. https://doi.org/10.1016/j.agee.2018.01.016

Rowley, M. C., Grand, S., & Verrecchia, É. P. (2018). Calcium-mediated stabilisation of soil organic carbon. *Biogeochemistry*, *137*(1–2), 27–49. https://doi.org/10.1007/s10533-017-0410-1

Ryo, M., & Rillig, M. C. (2017). Statistically reinforced machine learning for nonlinear patterns and variable interactions. *Ecosphere*, *8*(11), e01976. https://doi.org/10.1002/ecs2.1976

Sanderman, J., Hengl, T., & Fiske, G. J. (2017). Soil carbon debt of 12,000 years of human land use. *Proceedings of the National Academy of Sciences of the United States of America*, *114*(36), 9575–9580. https://doi.org/10.1073/pnas.1706103114

Schiedung, M., Tregurtha, C. S., Beare, M. H., Thomas, S. M., & Don, A. (2019). Deep soil flipping increases carbon stocks of New Zealand grasslands. *Global Change Biology*, *25*(7), 2296–2309. https://doi.org/10.1111/gcb.14588

Singh, S., Nouri, A., Singh, S., Anapalli, S., Lee, J., Arelli, P., & Jagadamma, S. (2020). Soil organic carbon and aggregation in response to thirty-nine years of tillage management in the southeastern US. *Soil and Tillage Research*, *197*, 104523. https://doi.org/10.1016/j.still.2019.104523

Six, J., Conant, R. T., Paul, E. A., & Paustian, K. (2002). Stabilization mechanisms of soil organic matter: Implications for C-saturation of soils. *Plant and soil*, *241*(2), 155–176. https://doi.org/10.1023/A:1016125726789

Six, J., Elliott, E. T., & Paustian, K. (1999). Aggregate and soil organic matter dynamics under conventional and no-tillage systems. *Soil Science Society of America Journal*, *63*(5), 1350–1358. https://doi.org/10.2136/sssaj1999.6351350x

Six, J., Elliott, E. T., & Paustian, K. (2000). Soil macroaggregate turnover and microaggregate formation: A mechanism for C sequestration under no-tillage agriculture. *Soil Biology and Biochemistry*, *32*(14), 2099–2103. https://doi.org/10.1016/S0038-0717(00)00179-6

Six, J., Elliott, E. T., Paustian, K., & Doran, J. W. (1998). Aggregation and soil organic matter accumulation in cultivated and native grassland soils. *Soil Science Society of America Journal*, *62*(5), 1367–1377. https://doi.org/10.2136/sssaj1998.03615995006200050032x

Six, J., Feller, C., Denef, K., Ogle, S. M., de Moraes, J. C., & Albrecht, A. (2002). Soil organic matter, biota and aggregation in temperate and tropical soils—Effects of no-tillage. *Agronomie*, *22*(7–8), 755–775. https://doi.org/10.1051/agro:2002043

Six, J., Frey, S. D., Thiet, R. K., & Batten, K. M. (2006). Bacterial and fungal contributions to carbon sequestration in agroecosystems. *Soil Science Society of America Journal*, *70*(2), 555–569. https://doi.org/10.2136/sssaj2004.0347

Smith, P. (2008). Land use change and soil organic carbon dynamics. *Nutrient Cycling in Agroecosystems*, *81*(2), 169–178. https://doi.org/10.1007/s10705-007-9138-y

Swiss Federal Research Stations. (1996). Schweizerische Referenzmethoden der Eidgenössischen Forschungsanstalten. In *Boden-und Substratuntersuchungen zur Düngeberatung (Issue 2)*. Agroscope Reckenholz-Tänikon.

Tiemann, L. K., Grandy, A. S., Atkinson, E. E., Marin-Spiotta, E., & McDaniel, M. D. (2015). Crop rotational diversity enhances belowground communities and functions in an agroecosystem. *Ecology Letters*, *18*(8), 761–771. https://doi.org/10.1111/ele.12453

Tisdall, J. M., & Oades, J. M. (1982). Organic matter and water-stable aggregates in soils. *Journal of Soil Science*, *33*(2), 141–163. https://doi.org/10.1111/j.1365-2389.1982.tb01755.x

Trabucco, A., & Zomer, R. (2019). Global aridity index and potential evapotranspiration (ET0) climate database v2. Figshare https://doi.org/10.6084/m9.figshare.7504448.v3

Treseder, K. K. (2004). A meta-analysis of mycorrhizal responses to nitrogen, phosphorus, and atmospheric CO_2 in field studies. *New Phytologist*, *164*(2), 347–355. https://doi.org/10.1111/j.1469-8137.2004.01159.x

Tsiafouli, M. A., Thébault, E., Sgardelis, S. P., de Ruiter, P. C., van der Putten, W. H., Birkhofer, K., Hemerik, L., de Vries, F. T., Bardgett, R. D., Brady, M. V., Bjornlund, L., Jørgensen, H. B., Christensen, S., Hertefeldt, T. D., Hotes, S., Gera Hol, W. H., Frouz, J., Liiri, M., Mortimer, S. R., … Hedlund, K. (2015). Intensive agriculture reduces soil biodiversity across Europe. *Global Change Biology*, *21*(2), 973–985. https://doi.org/10.1111/gcb.12752

van Bavel, C. H. M. (1950). Mean weight-diameter of soil aggregates as a statistical index of aggregation. *Soil Science Society of America Journal*, *14*(C), 20–23. https://doi.org/10.2136/sssaj1950.036159950014000C0005x

Wan, X., Chen, X., Huang, Z., & Chen, H. Y. H. (2021). Global soil microbial biomass decreases with aridity and land-use intensification. *Global Ecology and Biogeography*, *30*, 1056–1069. https://doi.org/10.1111/geb.13282

Watts, C. W., Whalley, W. R., Longstaff, D. J., White, R. P., Brook, P. C., & Whitmore, A. P. (2006). Aggregation of a soil with different cropping histories following the addition of organic materials. *Soil Use and Management*, *17*(4), 263–268. https://doi.org/10.1111/j.1475-2743.2001.tb00036.x

Weber, S. E., Diez, J. M., Andrews, L. V., Goulden, M. L., Aronson, E. L., & Allen, M. F. (2019). Responses of arbuscular mycorrhizal fungi to multiple coinciding global change drivers. *Fungal Ecology*, *40*, 62–71. https://doi.org/10.1016/j.funeco.2018.11.008

Wendt, J. W., & Hauser, S. (2013). An equivalent soil mass procedure for monitoring soil organic carbon in multiple soil layers. *European Journal of Soil Science*, *64*, 58–65. https://doi.org/10.1111/ejss.12002

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. *Scientific Reports*, *6*(1), 32525. https://doi.org/10.1038/srep32525

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. https://doi.org/10.1016/j.geoderma.2018.07.026

Williams, H., Colombi, T., & Keller, T. (2020). The influence of soil management on soil health: An on-farm study in southern Sweden. *Geoderma*, *360*, 114010. https://doi.org/10.1016/j.geoderma.2019.114010

Wilson, G. W. T., Rice, C. W., Rillig, M. C., Springer, A., & Hartnett, D. C. (2009). Soil aggregation and carbon sequestration are tightly correlated with the abundance of arbuscular mycorrhizal fungi: Results from long-term field experiments. *Ecology Letters*, *12*, 452–461. https://doi.org/10.1111/j.1461-0248.2009.01303.x

Zeder, J., & Fischer, E. M. (2020). Observed extreme precipitation trends and scaling in Central Europe. *Weather and Climate Extremes*, *29*, 100266. https://doi.org/10.1016/j.wace.2020.100266

Zeileis, A., Hornik, K., & Wien, W. (2008). Model-based recursive partitioning Torsten Hothorn. *Journal of Computational and Graphical Statistics*, *17*(2), 492–514. https://doi.org/10.1198/10618600SX319331

Zomer, R. J., Bossio, D. A., Sommer, R., & Verchot, L. V. (2017). Global sequestration potential of increased organic carbon in cropland soils. *Scientific Reports*, *7*(1), 15554. https://doi.org/10.1038/s41598-017-15794-8

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Edlinger, A., Garland, G., Banerjee, S., Degrune, F., García-Palacios, P., Herzog, C., Pescador, D. S., Romdhane, S., Ryo, M., Saghaï, A., Hallin, S., Maestre, F. T., Philippot, L., Rillig, M. C., & van der Heijden, M. G. A. (2023). The impact of agricultural management on soil aggregation and carbon storage is regulated by climatic thresholds across a 3000 km European gradient. *Global Change Biology*, *29*, 3177–3192. https://doi.org/10.1111/gcb.16677