Soil & Tillage Research 244 (2024) 106212

Contents lists available at ScienceDirect

Soil & Tillage Research

journal homepage: www.elsevier.com/locate/still

A geospatial approach for evaluating impact and potentiality of conservation farming for soil health improvement at regional and farm scale

Fabio Castaldi [a,*], Gabriele Buttafuoco [b], Flavio Bertinaria [c], Piero Toscano [a]

[a] National Research Council of Italy (CNR), Institute of BioEconomy, Via Giovanni Caproni 8, Firenze 50145, Italy
[b] National Research Council of Italy (CNR), Institute for Agricultural and Forest Systems in the Mediterranean, Via Cavour, 4-6, Rende, CS 87036, Italy
[c] Barilla G. e R. Fratelli S.p.A., Parma, Italy

ARTICLE INFO

Keywords:
Soil organic matter
Conservation agriculture
Farming system
Soil type
Croplands
Soil management

ABSTRACT

Soil organic matter (SOM) is a key factor in sustaining soil fertility, sequestering greenhouse gases and reducing soil erosion, in this regard, an accurate estimation and monitoring of the SOM content is crucial for sustainable land management and climate change mitigation strategies. In recent years, there has been a growing consciousness of the need to better understand the dynamics of SOM across different farm management in time and space.

In this context, the main objective of the study is to improve understanding regarding the relationship between SOM and the main farming systems adopted in Italy by taking spatial correlation into account. For this purpose, a large dataset consisting of topsoil SOM values (0–20 cm) and environmental and farming information was collected in 597 locations (145 fields and 62 farms) representative of the whole agricultural area of Po Valley in Italy. This sizable dataset was analyzed by a novel geospatial analysis using a de-clustering approach in combination with polygon kriging for detecting and understanding the SOM variability over the different fields characterized by irregular shapes and different farming systems.

The results provided clear evidences of the spatial correlation between SOM, farming systems and soil types. Higher SOM contents were detected in Cambisols (3.11 %) and in field managed according conservation agriculture practices (3.22 %) as compared to other farming systems. Moreover the inclusion of fodder crops in the rotation and the use of no-tillage are two of the most effective practices for increasing and preserving SOM according to our findings.

Spatial information, such those provided in this study, could facilitate the delineation of tailored solutions for each European Member State for targeting future actions related to carbon farming, and offering crucial insights to support advancements in agriculture for enhancing soil fertility and health and for fostering sustainable agricultural practices.

1. Introduction

Agriculture and the food systems are facing two challenges which are apparently contrasting: increasing food production continuing to erode social and natural systems or promoting environmental sustainability contributing to planetary well-being and resilience (IPCC, 2019). This situation of pressure has caused crises that can create opportunity for structural and systemic transformations to sustainability (Scoones et al., 2020).

Agriculture is both a contributor to and affected by climate change in Europe and it is responsible for 11 % of greenhouse gas emissions (Carsten et al., 2023). In this context, soil organic carbon (SOC) plays a crucial role in the health and functioning of terrestrial ecosystems, providing numerous benefits ranging from agricultural productivity to climate change mitigation. SOC is a key component of soil organic matter (SOM), which consists of plant and animal residues at various stages of decomposition, cells of soil microorganisms, and substances synthesized by soil organisms. SOM improves soil structure, aggregate stability and increases the water holding capacity, consequently, soils rich in carbon can help to delay or prevent the onset of the water surface

* Corresponding author.
E-mail address: fabio.castaldi@cnr.it (F. Castaldi).

https://doi.org/10.1016/j.still.2024.106212
Received 3 January 2024; Received in revised form 8 May 2024; Accepted 12 June 2024
Available online 14 June 2024

runoff after exceptional rainfall events (Falloon and Betts, 2010), which are more and more frequent as the recent and dramatic flooding in the Po river basin on May 2023 proves (Sabelli, 2023).

Given the importance of SOM in sustaining soil fertility, sequestering greenhouse gases, and maintaining ecosystem services, accurate and reliable monitoring of SOM is essential for sustainable land management and climate change mitigation strategies (Chenu et al., 2019; Schillaci et al., 2021).

Although the loss of organic carbon under agricultural land use is not universal, and modest gains can be seen when low-fertility soil is improved (Sanderman et al., 2017), in the vast majority of cases, the loss of organic carbon is more common. The decline in organic carbon stocks in agricultural soil can vary greatly across the globe due to factors such as soil properties, climate, type of land-use conversion, and especially the specific management practices used for a particular form of land use (Morais et al., 2019). The conversion of large areas of cultivated land to grassland would not only be unrealistic but also contrary to food security goals (De Rosa et al., 2023).

In recent years, there has been a growing awareness of the need to better understand the dynamics of SOM in soil across different farm management, spatial and temporal scales, as well as the factors driving its stability and vulnerability to changes in land use and climate conditions. Farming practices can significantly affect SOM levels and dynamics. Conventional agriculture often leads to SOM depletion due to intensive tillage, use of synthetic fertilizers, residues management, and other management practices that disrupt soil structure and microbial communities (Sanaullah et al., 2020). Organic farming, on the other hand, tends to promote soil health by avoiding synthetic fertilizers and pesticides, using cover crops and organic amendments (Babu et al., 2023; Gattinger et al., 2012). Conservation agriculture, compared to organic farming, is more focused on carbon sequestration, soil health restoration and biodiversity and reducing the risk of soil degradation practicing reduced tillage (Awale et al., 2013; Newton et al., 2020).

Recently Dupla et al. (2022) assessed the impact of different agricultural practices on SOC content changes over 10 years in Western Switzerland region finding out that organic matter inputs and cover-crop intensity were significantly correlated to SOC increase, while the soil tillage intensity and the soil saturation in carbon were correlated to SOC decrease. At the same time, they reported that conservation tillage and then no-till practices become necessary to further increase SOC contents. Previously González-Sánchez et al. (2012) concluded from a meta-analysis of data from 29 publications from Spain that no tillage and implementing cover crops can have positive effects on SOC. Govaerts et al. (2009) evaluating the effect of reduction in tillage intensity, retention of crop residues and use of crop rotations on SOC sequestration, finding out the reduction of tillage operations as main factor in reducing emissions from farming activities. Contrarily, evaluating the carbon sequestration over the whole soil profile (90 cm) and using soil samples from the long-term Wisconsin Integrated Cropping Systems Trials (WICST) across six different crop rotations, Sanford et al. (2012) found that all kinds of crop rotations lost soil carbon, even fields under no tillage, perennial forages, and cool-season grass pastures although to a lesser extent than fields under conventional tillage practices. The combination of a cool, humid climate in Wisconsin, and the already high soil carbon soils in southern Wisconsin place cropping systems in this study at a low potential for increasing SOC. Indeed, just across Lake Michigan at Michigan State's Kellogg Research Station, Syswerda et al. (2011) have shown an increase in carbon in the upper soil profile in no-till situations without losing carbon at depth.

Perego et al. (2019) showed how conservation agriculture, i.e. a set of agronomic practices including minimal soil disturbance (Palm et al., 2014), was able to increase soil fertility and economic efficiency on 20 farms in the Po valley. These substantial differences therefore appear to be linked to the climate in addition to the soil type. Warm and dry regions show the highest potential increase in sequestration from no-till and cover crops. The warmth stimulates more crop growth than in cool areas, which is returned to the soil, and the relative lack of rain means that soil carbon breaks down more slowly than in wet climates. Therefore, in order to investigate and obtain insights into the effects of agricultural systems and soil management on SOM concentration, the different edaphic and environmental conditions must be taken into account.

The Po river basin, covering 7 different regions in Central-Northern Italy, is the most important agricultural region in Italy and it contributes significantly to the national food supply, serving as a major source of staple crops. Consequently, understanding the variations in SOM content across the Po valley is crucial for assessing soil fertility, nutrient cycling, and sustainable agricultural practices. These variations can inform decision-making processes related to soil management strategies, including the application of organic amendments, conservation tillage, and crop rotation, aimed at promoting soil health and long-term agricultural sustainability. For this purpose, 597 soil samples were collected and analyzed for SOM content in topsoil layer (0–20 cm) representative of the soils and cropping systems of the whole agricultural area of Po Valley. Therefore, the main objective of the study is to compare the main farming systems adopted in Italy, i.e. conventional, organic (DG AGRI 2023) and conservation agriculture, which is understood here as the application of farming practices aimed at promoting soil health and biodiversity, in terms of SOM content, with the aim to figure out which are the more effective practices for SOM restoration.

Usually the comparison between different farming systems and their effects on soil properties, such as SOM, take place in field experiments at small scale, where the different treatments are generally allocated at random, thus assuming that observations of the response variable were uncorrelated or independent. However, the actual scenario in croplands is characterized by many fields scattered throughout the territory, and having different shapes and surface area and farming systems alternating spatially at short distances, consequently it is necessary taking into account the spatial correlation of SOM to properly compare the effects of different farming practices on this soil property.

In this regard, here we address the comparison between farming systems and practices in terms of SOM from farm to regional scale proposing an innovative geospatial approach to solve the problem of estimating the mean value of SOM over the different fields characterized by irregular shapes and clustered geographical distribution. This geospatial approach combines a de-clustering approach with polygon kriging (Buttafuoco et al., 2017), therefore estimating the expected value and standard deviation of the SOM for each field by taking spatial correlation into account. The suggested combined approach was never tested before, to the best of our knowledge, and it allowed to properly detect best practices and edaphic and environmental variables affecting the SOM distribution in croplands.

2. Materials and methods

2.1. The river Po basin

The Po river basin is characterized by a complex orography, about 50 % of its surface is covered by mountains (Alps in the north and Apennines in the south) while the rest of the area predominantly consists of flat plains. The basin covers the transition zone between the sub-continental climate of Central Europe and the Mediterranean climate, with an average annual precipitation of approximately 1200 mm (Beck et al., 2018) and great spatial variability due to the influence of different climatological regimes (Beniston, 2005). In parallel climate conditions in the Po area are changing in a sensitive way: from 1960 to present an increase of the annual mean temperature of about 2 °C has been observed, while an increase in the intensity of the single rainfall events, but an overall decrease in the total number of the rainfall events can be observed, resulting in a decrease of the annual mean precipitation of about 20 % observed during the last thirty years. The decrease is more evident during spring and summer seasons (when a maximum decrease of about 50 % can be noticed) whereas the inter-annual variability increases (http://www.feem-project.net/water2adapt/01_project_02.html. Accessed 1 September 2023).

The Po basin is one of the mostly populated areas in Italy and it is an intensely exploited area, accounting for 40 % of Italy's gross domestic product and 35 % of national agricultural production with farming systems generally intensive with high N input (Perego et al., 2014). The basin encompasses a diverse range of agricultural activities, including crop cultivation, livestock farming, and agro-industrial production, making it the primary agricultural region in Italy and it contributes significantly to the national food supply, serving as a major source of staple crops, such as wheat, corn, rice, and soybeans, as well as dairy and meat products.

The Po basin, covering 7 different regions, is divided into 81 districts (Geoportale del distretto Po, 2023), each exhibiting variations in terms of soil fertility that can be attributed to several factors, including variations in land use practices, soil management techniques, climate, soil types and topography. At the same time soil degradation processes are evident and affecting most of Po basin area (EU SOIL OBSERVATORY -EUSO Soil Health Dashboard, 2023).

The main soil types, according to the first level of the Food and Agriculture Organization (FAO) classification (IUSS Working Group, 2015) and extracted from the European Soil Database (Panagos et al., 2012), are Cambisols, Luvisols mainly in the western part of the basin and Fluvisols in the eastern part towards the coast, while Regosols are mainly located in the hilly regions of the right side of the river basin (Fig. 1).

2.2. Soil sampling survey

A soil sampling survey was carried out between 2021 and 2022, collecting 597 soil samples within 145 fields and 62 farms in flat cropland areas of the Po river basin from West Piemonte to the delta river close towards the Adriatic Sea. The soil sampling survey was conceived and planned to represent the three main agricultural managements insisting in this area (conventional, organic and conservation farming), and all the main soil classes insisting in the Po river basin (Fig. 1). Field classified as organic have been certified for between one and thirty-five years with an average time of ten years. All the fields within the conservation agriculture group, were interested by the application of some farming practices aimed at promoting carbon conservation/accumulation and biodiversity in soil: *i)* at least 5-years crop rotation including minimum three different crops, one of which is a leguminous, alternatively, 4-years rotation can be adopted if green manure and cover crop are used; *ii)* permanent or temporary grassed strips within the parcel having the minimum size of 3 % of the whole field. All these fields also hold certification for Sustainable Agriculture under the voluntary scheme of International Sustainability and Carbon Certification, ISCC Plus, the practices leading to recognition have been in place for between one and five years. Even though the application of no- or minimum-tillage is not mandatory for receiving this certification, the large majority of the selected fields in this work falling into the conservation agriculture class, adopted at least one of the two soil conservation practices. All the other fields not falling under the organic and conservation farming were indicated as conventional.

The abundance of soil samples collected within a certain soil type reflects the extent of that soil type in the investigated area: 406 samples in Cambisols (mostly Eutric, Calcic and Dystric Cambisols), 121 in Luvisols (mostly Orthic and Gleyic Luvisols) and 70 in Fluvisols (mostly Eutric Fluvisols) (Table 1). The samples taken within farms adopting conservation agriculture (CA) were 280, 172 insisting in fields managed according organic agriculture principles (OR) and 145 in conventionally managed fields (CO) (Table 2). For each sampling point, at least 5 subsamples within a radius of 5 m were picked up to a depth of 20 cm and put together in a bucket. After that, the soil was mixed in the bucket and a part of the composite sample was air-dried and sieved (2 mm) in the lab. SOC value was measured in the laboratory using the Walkley-Black method (Walkley & Black, 1934) for each sample and then transformed in SOM multiplying by 1.72 and then corrected according to Meersmans et al. (2009) correction factor to avoid the underestimation of SOM content provided by Walkley-Black method.

For each soil sample, several information were collected and reported in a database, including administrative (region, municipality, farm and field name), management (type of management, crop before the sampling, organic fertilization, tillage), geographical (field size, location, landscape, slope) and soil data (SOM, soil type).

2.3. SOM content comparison

2.3.1. Geospatial analysis

The geostatistical approach was used for the spatial modeling of SOM. Geostatistics (Matheron, 1971) consists of a set of models and methods for studying variables distributed in space, which exhibit both a structure and a random aspect. Any actual value of the target variable

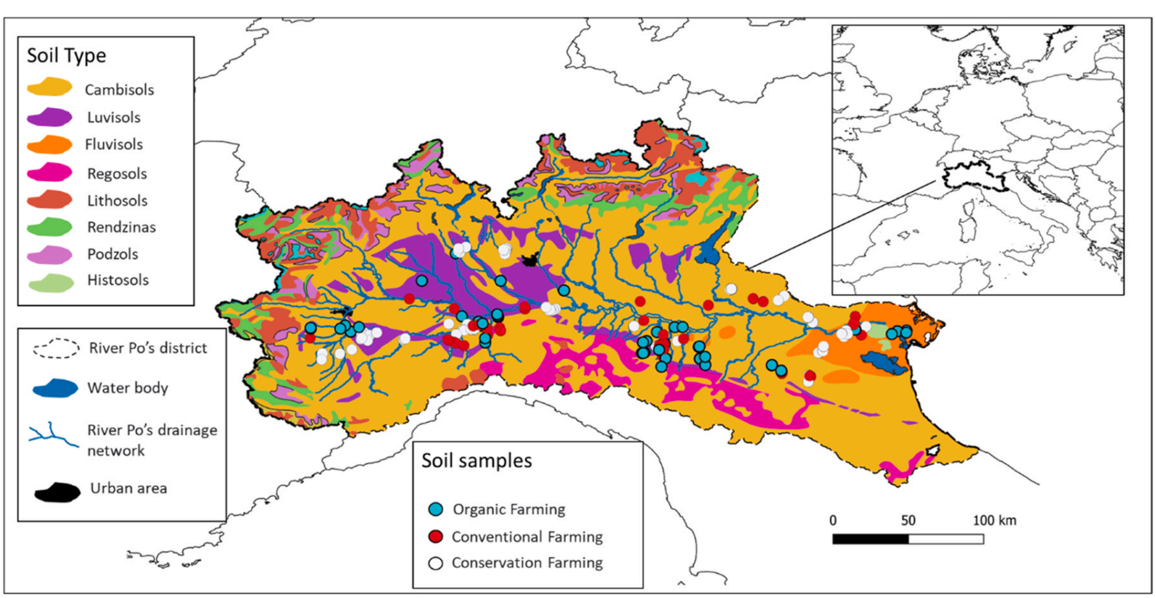

Fig. 1. River Po basin, soil types and location of the soil samples collected according to the three farming type (conventional, organic and conservation).

Table 1
Summary statistics for topsoil organic matter content (%) for soil type groups. The letters beside the mean values provide information concerning the significance of the differences between values ($p< 0.05$) obtained by post-hoc test.

Dataset	Group	Count	Mean		Median	Min	Lower quartile	Upper quartile	Max	Stand. dev.
Collected	Cambisols	406	3.11		2.89	0.83	2.22	3.67	11.45	1.24
	Fluvisols	70	2.84		2.63	0.99	2.2	3.53	5.81	1.06
	Luvisols	121	2.66		2.68	0.71	2.17	3.12	4.99	0.79
Augmented	Cambisols	406	3.11	a	2.89	0.83	2.22	3.67	11.45	1.24
	Fluvisols	406	2.83	b	2.66	0.99	2.2	3.53	5.81	1.02
	Luvisols	405	2.67	b	2.68	0.71	2.22	3.1	4.99	0.76

Table 2
Summary statistics for topsoil organic matter content (%) for farming management groups. The letters beside the mean values provide information concerning the significance of the differences between values ($p< 0.05$) obtained by post-hoc test.

Dataset	Group	Count	Mean		Median	Min	Lower quartile	Upper quartile	Max	Stand. dev.
Collected	Organic	172	2.82		2.64	0.83	2.09	3.42	6.66	1.02
	Conventional	145	2.71		2.49	0.71	2.09	3.27	5.38	0.95
	Conservative	280	3.22		2.99	1.14	2.41	3.71	11.45	1.26
Augmented	Organic	280	2.83	b	2.65	0.83	2.09	3.43	6.66	1.02
	Conventional	280	2.71	b	2.49	0.71	2.09	3.26	5.38	0.94
	Conservative	280	3.22	a	2.99	1.14	2.41	3.71	11.45	1.26

(SOM in this study) is considered as the outcome (realization) of a random variable, $Z(\mathbf{x})$, and called regionalized variable, $z(\mathbf{x})$, here, $\mathbf{x}$ is the location coordinates vector (x, y). The set of spatially dependent random variables, $Z(\mathbf{x})$, forms the random function. The random variable is denoted with capital Z, whereas its outcome (regionalized variable, $z(\mathbf{x})$) is denoted with lowercase z. The values of the regionalized variable, $z(\mathbf{x})$, at unsampled locations are unknown, but they well defined and also considered as realizations (outcomes) of the same random variable $Z(\mathbf{x})$ (Armstrong, 1998).

The basic tool for structural interpretation of the variable under study and for its estimation at unsampled locations is the variogram (Matheron 1971), which is a function of the vector $\mathbf{h}$ (module and direction) (lag). The variogram quantifies how different the values become as the distance increases for a defined direction and allows to define spatial isotropic or anisotropic behaviors. However, the calculated variogram (called experimental) consists in a set of unconnected points and being used to predict the variable at unsampled locations, it needs to be fitted by a continuous mathematical function (model) to calculate variogram values for any distances and not obtain negative variances for any combination of random variables (Armstrong, 1998; Webster and Oliver, 2008). To meet this latter constraint, only a limited number of theoretical model types known as authorized variograms can be used. The most used variogram models are defined by two parameters: range and sill. The first is the distance over which pairs of variable values are spatially correlated, while the second (sill) is the variogram value corresponding to the range. A cross-validation is used to choose the variogram model having an optimal fitting. Cross-validation checks the compatibility between the data and the variogram model by considering each data point in turn, removing it temporarily from the dataset and using its neighboring information to predict the value of the variable at its location. Mean error (ME) and mean squared deviation ratio (MSDR) are used to evaluate the goodness of the fitting (Webster and Oliver, 2008).

Even though the geostatistical approach does not require the data follow a normal distribution, variogram modeling is sensitive to strong departures from normality because a few exceptionally large values may contribute to many very large, squared differences. Therefore, a data transformation is suggested when skewness is greater than 0.5 (Webster and Oliver, 2008) and Gaussian anamorphosis is a suitable procedure to transform skew data into a Gaussian-shaped variable with zero mean and unit variance (Chilès and Delfiner, 2012; Wackernagel, 2003).

Moreover, to avoid artefacts in the calculation of the experimental variogram due to groups of soil samples compared to other isolated ones, a declustering procedure was applied (Chilès and Delfiner, 2012). The principle of the declustering application is to assign a weight w_i to each sample where a given variable is defined taking possible clusters of samples into account. To compute the weight w_i to be associate to a target sample i, the number n_i of soil samples inside a moving window centered on this target sample is counted. The weight w_i is equal to m_v/n_i where m_v is the mean of all the n_i. The weight will be 1 when the number of points inside the moving window equals the mean of the n_i.

The variogram fitted by the declustering procedure was used with Polygon kriging (Buttafuoco et al., 2017) and all data to estimate an average value of SOM and its associated variance of estimation over each of the irregular shaped fields. Polygon kriging is used when the estimation has to be made over polygon of irregular shape and different size and it is an almost straightforward extension of block kriging (Webster and Oliver, 2008). Polygon kriging requires that each polygon is firstly discretized in a number of regular cells i, then the average covariance function relative to each polygon v, is calculated as a weighted discrete summation of the point covariance function:

$$K_{\alpha v} = \frac{1}{\sum_{i=1}^{N_c} \rho_i} \sum_{i=1}^{N_c} w_i K_{\alpha c_i} \tag{1}$$

where each r_i relates to the proportion of the intersection area between the cell i, centered in the point c_i and the polygon v, N_c is the number of the cells i within the polygon v, α is a data point, $K_{\alpha c_i}$ is the covariance function calculated at each point c_i and $K_{\alpha v}$ is the average point-area covariance relative to the polygon v.

To assess the estimation uncertainty of the average values for SOM in the three farm management types, their confidence intervals (CI) were calculated. The confidence intervals reflect the inability to exactly define un unknown value and its uncertainty increase with the CI size. A 95 % confidence level was used and the upper and lower limits of the CI were defined in terms of standard deviation (SD):

$$\begin{aligned} Upperlimit &= Averagevalue + 1.96SD \\ Lowerlimit &= Averagevalue - 1.96SD \end{aligned} \tag{2}$$

The calculation of CI requires that the input values are normally distributed, otherwise they have to be converted into Gaussian values. Both the average values and standard deviation estimated by polygon kriging for each polygon (fields) are Gaussian values. After the calculation of the upper and lower limits for each average value estimate, were back transformed into the raw values.

All geostatistical analyses were performed using the software package Isatis.neo, release 2023.04 (Bleines et al., 2018).

2.3.2. Analysis of variance

A first exploratory test was conducted to evaluate the effects on SOM (the variable of interest) of control factors, that is all the variables that could affect the SOM content. For this purpose a multi-way analysis of variance (ANOVA) was carried out; in this study we considered as control factors and categorical variables for the ANOVA the soil type, fertilization type (mineral+organic or organic), tillage (conventional, minimum, no tillage) farm management (conventional, organic and conservation, pre-sampling crop according to EUROSTAT classification (Eurostat: Technical reference document C-3: Classification Land cover and Land use, 2015) and Po river hydrographic districts.

In addition to the spatial analysis, the means of SOM content was compared among homogenous groups by all the control factors having significant correlation with SOM according the ANOVA results. Due to the different abundance of samples within the different groups, a data augmentation was performed creating artificial samples within the minority groups by the Synthetic Minority Oversampling Technique (SMOTE) (Chawla et al., 2011) using a nearest neighbors approach. The augmented datasets were transformed for normality by a box-cox transformation. The homoscedasticity assumption was checked on transformed data by the Bartlett's test, if the assumption was verified, the ANOVA model and a Tukey post-hoc test were carried out for detecting differences between groups ($p<0.05$), while a one-way ANOVA plus Games-Howell post-hoc test were performed if the homoscedasticity assumption was not verified. All the analyses relate to the ANOVA were performed using R software (R Core Team, 2022)

The soil samples collected within the river Po basin were split into four soil aggregate stability classes according their SOM content. The SOM thresholds were defined combining the classification of Greenland et al. (1975), also reported in Loveland and Webb (2003), with the organic content classes indicated by EIP-AGRI Focus Group Soil Organic Matter in Mediterranean regions (2015). The resulting classes are: (i) very unstable with SOM < 1.72 %; (ii) unstable from 1.72 % to 3.4 % of OM; (iii) stable from 3.5 % to 4.3 %; (iv) very stable with OM >4.3 %. For each SOM control factor, the Δ% within each aggregate stability class was expressed as difference between the observed frequency and the frequency of the investigate group in the whole dataset. This variable is useful to figure out if a certain group (e.g. samples collected in Cambisols) has a frequency for a given aggregate stability class higher or lower than the general frequency.

3. Results

3.1. The soil dataset

Most of the soil samples (390) has a SOM content falling in the unstable class (Fig. 2), in accordance with the map of organic carbon content in topsoil of Europe (Jones et al., 2005). The most frequent pre-sampling crops are cereals, mostly common wheat and maize, then non-Permanent industrial crops, mainly soy bean, sunflower, rapeseed and basil (Table 3). Concerning the fertilization, 342 samples were collected in fields where mineral+organic fertilizers were applied, and 251 where organic fertilizers were primarily used. A large variety of organic fertilizers were registered in the dataset: cow and poultry manure, biogas and barn slurry, compost, digestate, green manure, etc. Conventional tillage, is the most common type, minimum tillage is also widely used, while pure no tillage, i.e. not alternating with minimum or conventional tillage interests few locations (Table 4).

3.2. Correlation between SOM and control factors

The ANOVA highlighted a significant correlation between SOM and soil types, farming types, pre-sampling crop and tillage ($p<0.01$), while no correlation was detected between the variable of interest and the fertilization types (Table 5). However, fertilization showed significant correlation with SOM in combination with soil types and together with farming and pre-sampling crop. The highest F values were obtained for tillage and the combination of tillage and farming type.

3.3. SOM content comparison between farming types

Tables from 1 to 4 show the summary statistics for SOM and their comparisons between groups of the investigated factors. Concerning farming types, CA showed an average SOM content significantly higher than OR and CO. A strong positive Δ% (∼ +10 %) in the better aggregate stability classes and a highly negative Δ% (close to −20 %) for very unstable soils were detected for CA farming (Fig. 3a). An inverse trend was observed for OR and CO as compared to CA. However, in order to check whether the time elapsed since the adoption of the farming protocol, i.e. CA or OR, has had an influence on SOM content, we split OR and CA datasets according to years: from 0 to 2 years (OR 1 and CA 1),

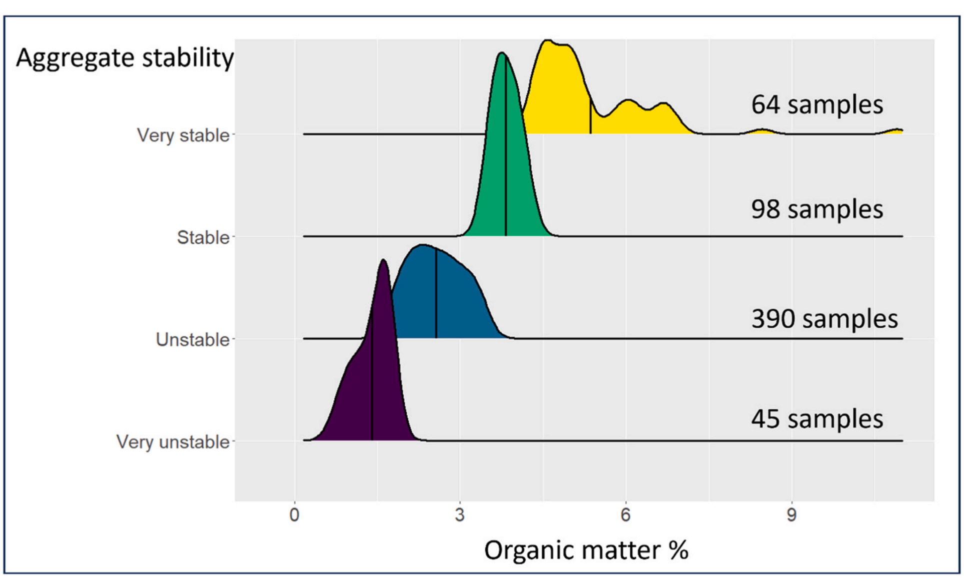

Fig. 2. Probability density function plots of topsoil organic matter percentage of the whole soil dataset according to aggregate stability classes.

Table 3
Summary statistics for topsoil organic matter content (%) for pre-sampling crop groups. The letters beside the mean values provide information concerning the significance of the differences between values (p< 0.05) obtained by post-hoc test.

Dataset	Group	Count	Mean		Median	Min	Lower quartile	Upper quartile	Max	Stand. dev.
Collected	Cereals	372	3.06		2.83	0.71	2.18	3.64	3.64	1.27
	Dry pulses, vegetables and Flowers	89	2.77		2.88	0.83	2.13	3.44	3.44	0.85
	Fodder crops	28	3.81		3.91	1.85	2.88	4.53	4.85	1.12
	Non-permanent industrial crops	108	2.67		2.58	1.08	2.22	2.97	2.97	0.74
Augmented	Cereals	372	3.06	b	2.83	0.71	2.18	3.64	3.64	1.27
	Dry pulses, vegetables and Flowers	372	2.76	c	2.88	0.83	2.13	3.43	3.44	0.84
	Fodder crops	372	3.79	a	3.92	1.85	2.84	4.54	4.86	0.99
	Non-permanent industrial crops	372	2.67	c	2.58	1.08	2.22	2.98	2.95	0.7

Table 4
Summary statistics for soil organic matter content (%) for soil tillage groups. The letters beside the mean values provide information concerning the significance of the differences between values (p< 0.05) obtained by post-hoc test.

Dataset	Group	Count	Mean		Median	Min	Lower quartile	Upper quartile	Max	Stand. dev.
Collected	Conventional tillage	317	2.84		2.68	0.99	2.11	3.53	6.66	0.97
	Minimum tillage	235	3.04		2.85	0.71	2.31	3.51	10.9	1.24
	No tillage	45	4.47		4.01	2.5	3.26	5.68	8.46	1.6
Augmented	Conventional tillage	317	2.84	b	2.68	0.99	2.11	3.53	6.66	0.97
	Minimum tillage	317	3.06	b	2.87	0.71	2.33	3.52	10.9	1.19
	No tillage	317	4.46	a	3.98	2.5	3.22	6.14	8.46	1.52

Table 5
Results of the analysis of variance (ANOVA) conducted to evaluate the effects of soil type, tillage, fertilization, farming type and pre-sampling crop on soil organic matter (the variable of interest. *** p<0.001; **p<0.01; *p<0.05; ns =not significant.

Control factors	F value	Pr (>F)
Tillage	39.15	***
Soil	12.58	***
Fertilization	2.86	ns
Farming	11.16	***
Pre-sampling crop	13.03	***
Tillage: Soil	2.15	*
Tillage: Fertilization	5.26	**
Soil: Fertilization	7.87	***
Tillage: Farming	39.74	***
Soil: Farming	5.68	***
Fertilization: Farming	3.39	*
Tillage: Pre-sampling crop	11.88	***
Soil: Pre-sampling crop	1.91	*
Fertilization: Pre-sampling crop	1.02	ns
Farming: Pre-sampling crop	9.16	***
Tillage: Soil: Fertilization	5.62	***
Tillage: Soil: Farming	9.5	***
Tillage: Fertilization: Farming	2.16	ns
Soil: Fertilization: Farming	9.92	***
Tillage: Soil: Pre-sampling crop	3.18	*
Tillage: Fertilization: Pre-sampling crop	2.36	ns
Soil: Fertilization: Pre-sampling crop	4.51	*
Tillage: Farming: Pre-sampling crop	2.72	ns
Soil: Farming: Pre-sampling crop	0.71	ns
Fertilization: Farming: Pre-sampling crop	20.68	***

from 3 to 5 years (OR 2 and CA 2) and more than 5 only for OR (OR 3), while no farms available that had adopted RE practices for more than 5 years. The statistical comparison reported in Table 6 highlighted how the average SOM content is significantly higher in CA 2 (3.64 %) than all the other groups.

The crossing comparison between farming types and soils confirmed the significantly higher SOM values for CA in Cambisols and Luvisols, while no difference between the three groups were detected in Fluvisols (Table 7).

Considering all the SOM data together, they showed a clear positive asymmetry with a skewness of 1.5. Therefore, to model and quantify their spatial variability, SOM data were transformed into standardized Gaussian values. Moreover, as explained in the methods section, a declustering procedure was applied to avoid artefacts in the calculation of the experimental variogram because of soil samples that were very close (clustered) compared to others that were very far apart. From the Gaussian SOM data, a map of 2D variogram (not shown) was computed and no relevant difference as a function of direction was found. The experimental variogram looked upper bounded with a clear presence of variation at two different spatial scales (Fig. 4). Therefore, the fitted nested theoretical model included a nugget effect and two isotropic spherical models (Webster and Oliver, 2007) at short (about 11,000 m) and longer (about 77,000 m) range. The nugget effect is the positive intercept in the variogram (Fig. 4), which can arise from errors of measurements and spatial variation within the shortest sampling interval (Webster and Oliver, 2008). The results of goodness fitting provided by cross-validation were satisfactory because the mean error was close to zero (-0.006) and standardized error variance equal to 1.

Then, this variogram was used within polygon kriging to compute for each experimental field, the expected SOM value and its standard deviation. The boxplots of SOM expected values (Fig. 5a) and related standard deviations of estimation (Fig. 5b) obtained from polygon kriging are reported in Fig. 5. A greater variability of expected SOM values was obtained for CA, while less variability was obtained for CO. Indeed, the spread of the expected values is greater for CA (stand. dev. = 1.03 % and IQR=1.37 %) than for OR (stand. dev. = 0.92 % and IQR=1.26 %) and CO (stand. dev. = 0.89 % and IQR=1.21 %) both in terms of standard deviation and interquartile range (Fig. 5a). The least dispersion was achieved for CO. Concerning the means and medians of the SOM expected values (Fig. 5a), the means are always greater than the medians with the maximum difference for OR (0.26 %) followed by CA (0.13 %) and CO (0.11 %).

Conversely, the variability of the standard deviation of estimation is lowest for CA (0.06 %), followed by CO (0.05 %) and OR (0.11 %) (Fig. 5b). The standard deviation of estimation does not depend on data values, but on the configuration of the sampling points in relation to the target point of estimation and on the variogram (Webster and Oliver, 2008). Intuitively, the accuracy of an estimate is lower in more variable areas than in those with low variability. Therefore, one interpretation might be the lower variability of SOM values locally for CA than for OR and CO.

Another way to assess the results of polygon kriging and estimate the uncertainty of the average values for SOM in the three cropping systems,

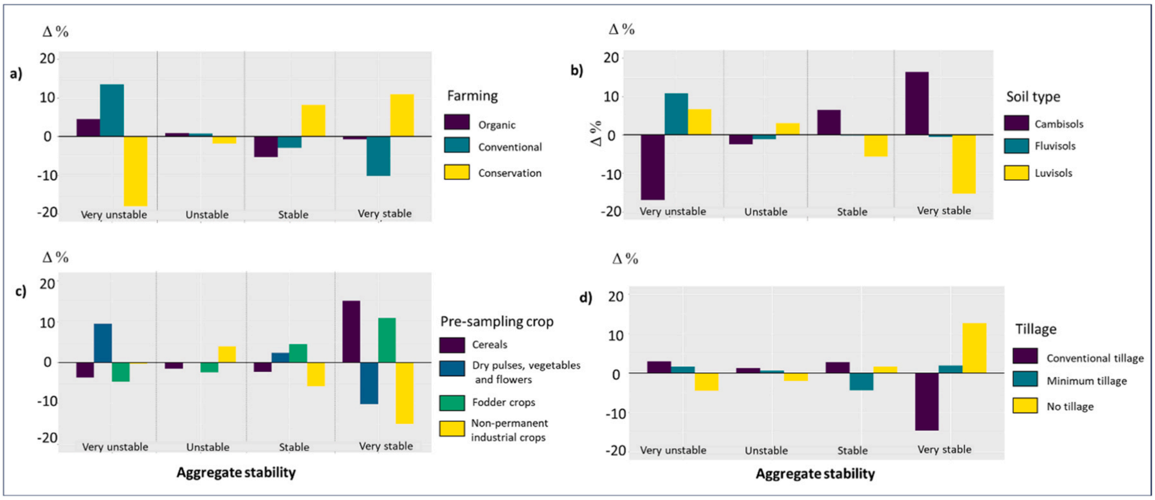

Fig. 3. Percentage variation (Δ%) within each aggregate stability class expressed as difference between the observed frequency and the frequency of the investigate group in the whole dataset for farming type (a), soil type (b), pre-sampling crop (c) and tillage (d).

Table 6
Summary statistics for topsoil organic matter content (%) for each farming type subsets according to the years since the farming type was adopted. The letters beside the mean values provide information concerning the significance of the differences between values ($p < 0.05$) obtained by post-hoc test. * OR=organic farming; CO= conventional farming; CA= conservation farming.

Dataset	Group	Years	Count	Mean		Median	Min	Lower quartile	Upper quartile	Max	Stand. dev.
Collected	OR1	0–2	25	2.98		3.16	0.99	2.22	3.56	5.00	0.96
	OR 2	3–5	68	2.93		2.49	1.52	2.09	3.91	5.00	1.02
	OR 3	>5	79	2.68		2.57	0.83	2.03	3.06	6.66	1.04
	CA 1	0–2	144	2.82		2.68	1.30	2.22	3.30	6.48	0.87
	CA 2	3–5	136	3.65		3.37	1.14	2.71	4.04	10.9	1.47
	CO		145	2.71		2.49	0.71	2.09	3.27	5.38	0.95
Augmented	OR1	0–2	144	3.03	b	3.18	0.99	2.22	3.61	5.00	0.83
	OR 2	3–5	144	2.95	b	2.46	1.52	2.09	3.95	5.00	1.02
	OR 3	>5	145	2.67	b	2.57	0.83	2.03	3.09	6.66	1.01
	CA 1	0–2	144	2.81	b	2.68	1.30	2.22	3.30	6.48	0.87
	CA 2	3–5	144	3.64	a	3.42	1.14	2.71	4.01	10.90	1.44
	CO		145	2.71	b	2.49	0.71	2.09	3.27	5.38	0.95

Table 7
Summary statistics for topsoil organic matter content (%) for each combination of farming type and soils. The letters beside the mean values provide information concerning the significance of the differences between values ($p < 0.05$) obtained by post-hoc test. * OR=organic farming; CO= conventional farming; CA= conservation farming.

Soil type	Dataset	Group	Count	Mean		Median	Min	Lower quartile	Upper quartile	Max	Stand. Dev.
Cambisol	Augmented	OR	199	2.92	b	2.68	0.83	2.04	3.68	6.66	1.08
		CO	198	2.84	b	2.65	1.08	2.12	3.50	5.38	0.95
		CA	199	3.34	a	3.04	1.48	2.47	3.84	10.90	1.37
Fluvisol	Augmented	OR	32	2.87	a	2.73	0.99	2.25	3.22	5.00	1.14
		CO	32	2.97	a	2.82	1.93	2.35	3.46	4.74	0.79
		CA	32	2.67	a	2.41	1.14	1.99	3.46	5.81	1.07
Luvisol	Augmented	OR	48	2.56	b	2.50	1.30	2.17	2.84	4.42	0.58
		CO	49	2.06	c	2.14	0.71	1.60	2.52	3.77	0.79
		CA	49	3.09	a	3.09	1.30	2.68	3.54	4.99	0.71

was to calculate the 95 % confidence intervals (Eq. 2). From the visual inspection of Fig. 6, the variability and uncertainty of the expected values in individual plots is clear. Indeed, there is a certain dispersion of results and no particular trend is evident in any of the three cropping systems.

However, it is equally clear that the average expected value of SOM is generally higher in CA. This is also shown in Fig. 5, in which both the mean and median of the expected SOM values are higher in CA than in OR and CO. Furthermore, considering the average of all expected values of SOM (2.91 %) in the three cropping systems, the proportion of times in which the expected value of SOM is higher than the above average is 49.3 % in CA, 33.3 % in OR and 27.3 % in CO. This result provides clear indications of a trend towards higher values for CA.

3.4. SOM comparison according to other parameters

3.4.1. Soil types

Samples collected in Cambisols have a wide range of SOM content and the average value is significantly higher than those observed in Luvisols and Fluvisols (Table 1). Cambisols and Luvisols showed opposite behavior in Fig. 3b: Cambisols have positive Δ% in Stable and Very stable (>15 %) classes where Luvisols showed negative values (-15 % in

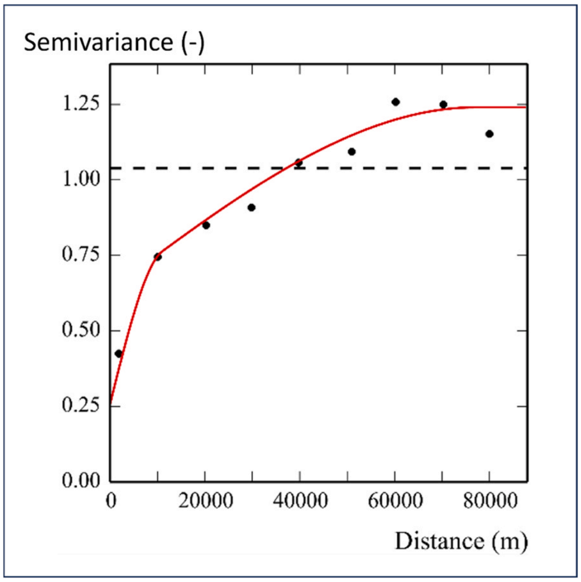

Fig. 4. Experimental variogram (filled black dots) and fitted theorical model (solid red line) of Gaussian soil organic matter values. The experimental variance (black dashed line) is also reported.

Very stable). On the contrary, for the Very unstable class, Fluvisols and Luvisols showed positive Δ% and Cambisols a strong negative value close to −20 %.

Going into more detail into soil classes, the SOM content values were compared also between groups made up from the second level of FAO soil classification (Fig. 7). The average SOM values of Orthic Luvisols (3.40 %) and Calcic Cambisols (3.78 %) are significantly higher than the other classes, while the lowest value was found for Dystric Cambisols (2.12 %) (Fig. 7). Concerning the distribution of farming systems according sol types, the highest frequency for CO was observed in Dystric Cambisols (50 %), for CA in Calcic Cambisols (75 %), while the frequency of OR ranges between 30 % and 40 % for all soil types except in Dystric Cambisols and Calcic Cambisols where no OR soil samples were collected (Fig. 8).

3.4.2. *Pre-sampling crops*

Table 3 shows a significantly higher SOM content in field interested by fodder crops before the soil sampling as compared to cereals, Dry pulses, vegetables and flowers and non-permanent industrial crops. Cereals and Fodder crops show the highest positive Δ% in the very stable group, while, in the same group, dry pulses, vegetables and flowers category and non-permanent industrial crops have strongly negative Δ% (Fig. 3c).

3.4.3. *Tillage*

SOM content observed in no tillage fields showed a significantly higher than the other two tillage types, while no significant differences were detected between conventional and minimum tillage (Table 4). The highest positive Δ% in very stable class was observed for no tillage (+12 %), while the conventional tillage showed a negative Δ value around 15 % (Fig. 3d). Minimum tillage showed a slightly positive Δ in all the aggregate stability classes except in stable class.

4. Discussion

Across all the soil samples included in this study spanning over 145 fields and 62 farms representative of the soils and cropping systems of the whole agricultural area of Po Valley in Italy, SOM is 13.8 % and 18.8 % higher in CA compared to OR and CO respectively. This result agrees well with the previous findings in literature (Govaerts et al., 2009; Ogle et al., 2012; Perego et al., 2019; Stavi et al., 2016; Virto et al., 2012). Our study, covering a vast area, demonstrates the highly variable and uncertain response of SOM to different agricultural management practices. As indicated by the ANOVA analysis, soil type, farming type, tillage and the crop preceding the soil sampling exhibited significant correlations with SOM levels. Conversely, various fertilization treatments and hydrographic districts did not show any notable impact on SOM.

Regarding fertilization treatments (organic and organic+mineral), our results contradict those of Guo et al. (2019), who reported significant effects of fertilization treatments over a 22-year period in a field, with organic and organic-inorganic fertilizers significantly increasing SOC content. However, our findings align with other studies in the literature, including long-term analyses on topsoil (0–20 cm), such as

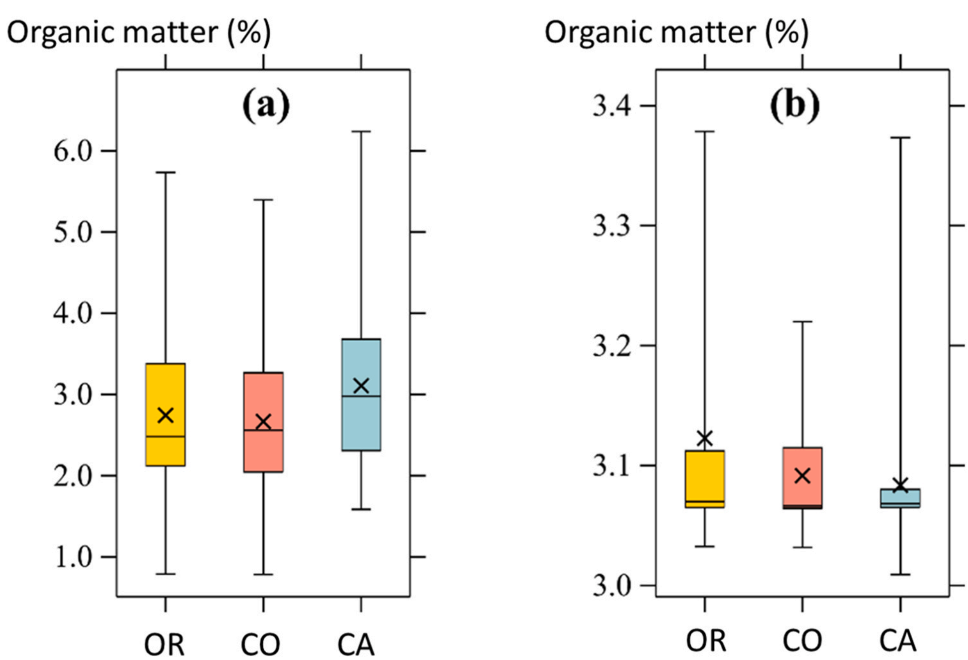

Fig. 5. Boxplots of topsoil organic matter expected values (a) and standard deviations of estimation (b) obtained from polygon kriging.

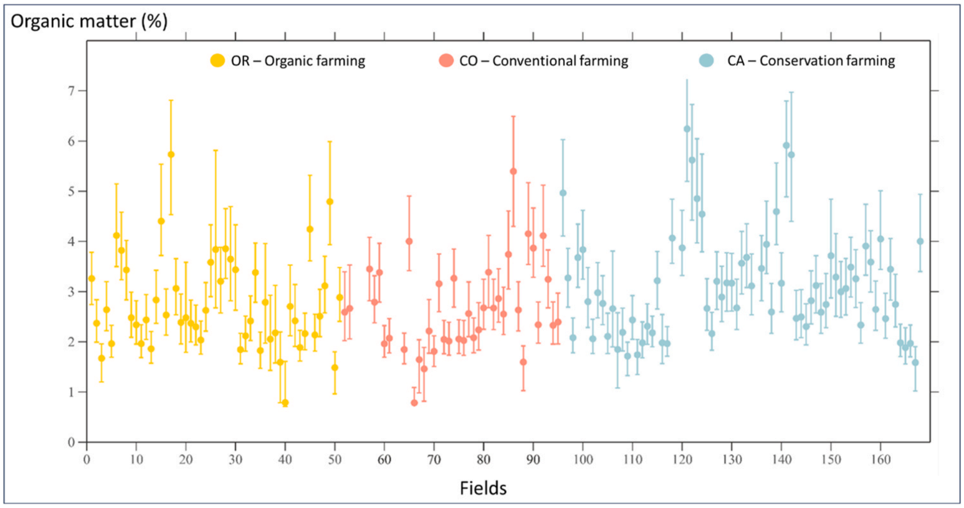

Fig. 6. Expected value (solid circles) and 95 % confidence intervals (vertical lines bordered by a horizontal dash) of the topsoil organic matter (SOM) in the plots submitted at the three cropping systems.

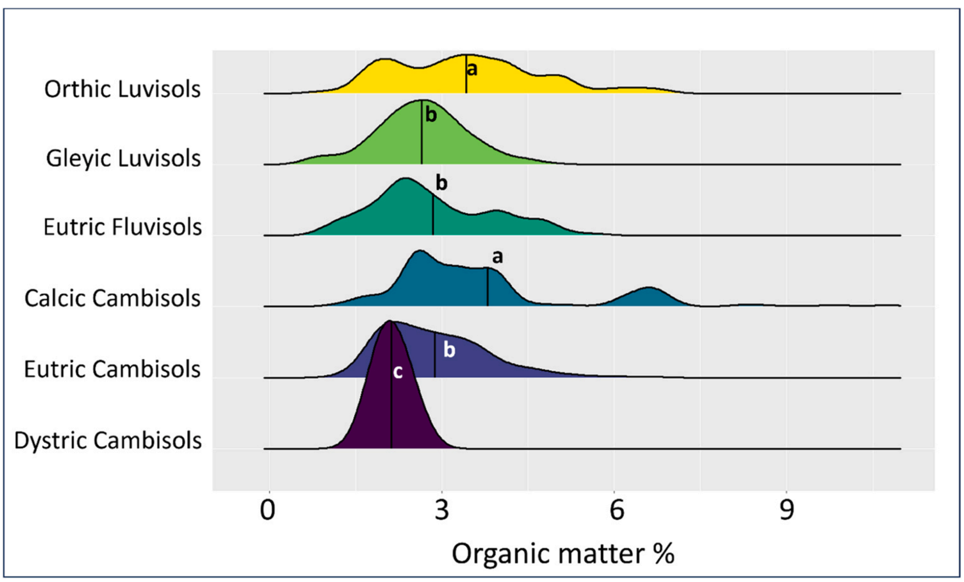

Fig. 7. multiple density plots for topsoil organic matter content (%) for each Level 2 soil type considering the augmented dataset. The black vertical lines indicate the mean values. The letters close each plot indicate if significant differences exist between the mean values.

Wu et al. (2019) and Liliana et al. (2020). Nonetheless, the ANOVA showed that fertilization can be a key factor for SOM content, but only in combination with other factors such as soil type, pre-sampling crop and tillage (Table 5).

Among the significant factors, the crop preceding soil sampling showed distinct clustering. Notably, the average SOM value for fodder crops was significantly higher than for other crop types. Furthermore, all samples with a previous crop of fodder crops were either in the OR or CA categories, with a significant difference in SOM content (6.2 % for CA and 3.3 % for OR). This different response to the use of fodder crops before soil sampling between CA and OR could be explained observing the soil types insisting in the two categories; all the CA fields, where fodder crop grew before the sampling, insist in Orthic Luvisols, that is the soil type characterized by the highest average SOM content (Fig. 8), while the OR fields mostly fall within poorer soils. In a recent meta-analysis, Zheng et al. (2023) quantitatively assessed crop rotation-induced changes in soil aggregation and associated SOC based on 2199 paired observations from 53 studies. They found that crop rotation effects are particularly pronounced when the previously cultivated crop was soybean, this finding contrasts with our results, but it's essential to note that their analysis only included alfalfa as a fodder crop in crop rotation.

In our study area, Cambisols, Luvisols, and Fluvisols are the dominant soil types. Generally, average SOM content is higher in Cambisol than in Fluvisols and Luvisols, with the latter typically having the lowest values. These results are consistent with findings reported by Calvo de Anta et al. (2020) for Spanish agricultural areas (1.2 %, 1.0 %, 0.6 % SOC for Cambisols, Luvisols, and Fluvisols, respectively) and differ from those of Munoz-Rojas et al. (2012), where Cambisols generally exhibited lower SOC values than Fluvisols and Luvisols. Extracting the average value for each soil type insisting within the Po basin from the map of the topsoil organic carbon content of Europe (de Brogniez et al., 2015), Cambisols showed highest values (SOC=3.2 %) as compared to the other two soil types (2.3 %). However most of the regions interested by woodlands insist on Cambisols and this could strongly influence the average SOC content; in fact, selecting only the regions interested by the

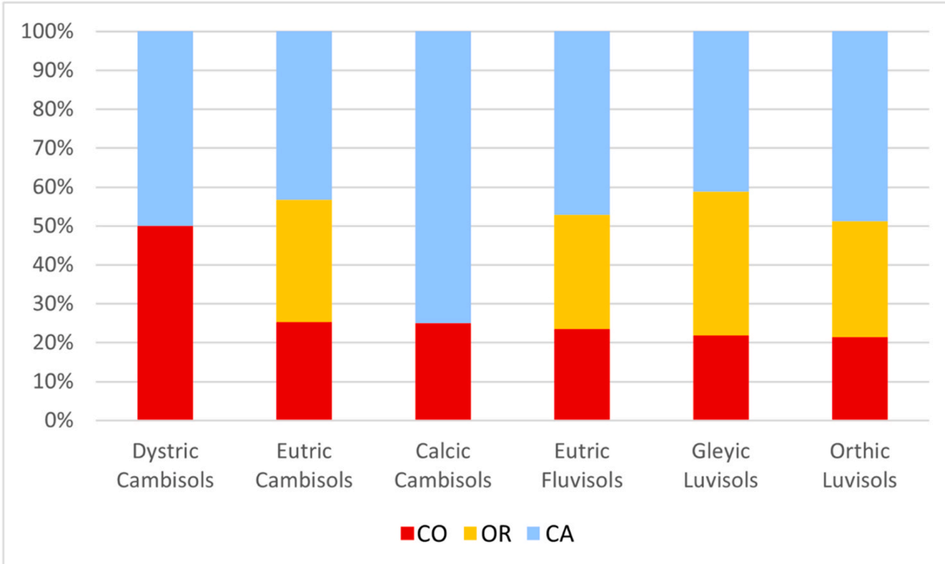

Fig. 8. Frequency of each farming type (CO=conventional; OR=organic; CA=conservation) within the six soil types.

soil dataset, therefore only croplands, the differences among soil types level off, showing average values around 2 % for all the three soil types. CA samples showed the highest average SOM content among farming types for Luvisols and Cambisols, while for Fluvisols there are no significant differences (Table 7), this could be due to the low number of samples collected within these soils, more in particular, the samples collected in CO, that have the highest SOM average value (3.01 %), are only localized in a narrow area close to the Po delta, and generally characterized by high carbon stock values according to the European map of the current SOC stock produced by Yigini and Panagos (2016) and derived by LUCAS topsoil data. De Rosa et al. (2023) produced the map of yearly rate of SOC stock changes (Δ SOCc) in topsoil in Europe between 2009 and 2018, and, although this is a time interval prior to the creation of our dataset, we extracted the map values corresponding to sampling points to observe whether there are different potentials between soil types. We found an average Δ SOCc close to 0 g C kg^{-1} $year^{-1}$ for most of the soil types, while for Eutric Cambisols an average increase of 0.11 has been observed and 0.06 for Eutric Fluvisols, therefore we could infer that these two soil types in this region have a higher SOC storage potential as compared to the other soils. Observing the European clay map produced by the European Soil Data Center (ESDAC) (Fernandez et al., 2022), both Eutric Fluvisols and Eutric Cambisols fall in clay-rich regions, and high soil clay content have a positive influence on Δ SOCc (De Rosa et al., 2023), especially where the initial SOC content is not very high. Also Zheng et al. (2023) have identified initial SOC value as one of the most influential factor, together with climate, for carbon increase in soil. Even though Eutric Cambisols are among the most productive soils in agriculture according FAO, they did not show the highest SOM values within the investigated region, therefore a further improvement in terms of SOC stock may be expected for croplands insisting in these soils.

Perego et al. (2019) compared conservation and conventional farming system in 20 farms distributed across a very large region, however these farms are far away from each other and the comparison of soil and crop parameters occurred in each farm individually, thus properly assuming that observations of the response variables were uncorrelated or independent. However, the reality of large agricultural areas is quite different from a controlled field experiment, and the soil properties are generally spatially correlated, i.e. close measurements should be more similar than those made at greater distances. Therefore, we have taken the spatial correlation of SOM values across the Po river basin into account by the combined geospatial approach, highlighting that their spatial variation is not random and can be modeled by a variogram. Two different spatial scales of variation have been observed and have been modeled by a nested variogram in which different theorical models (structures) have been combined. The first spatial structure has a range of 11 km, which describes a local scale, probably limited by differences in farming and geomorphological features, and a second spatial structure which runs out at a distance of 77 km, thus at regional scale, that could be mainly determined by differences in soil type. However, soil type alone does not determine SOM content, but by its combination with agricultural management. Therefore, for a specific soil type to express its full potential in terms of SOM storage, it needs to be properly managed, and this study clearly highlighted as farming system is one of the main key factor for SOM content storage in croplands. A review of the main agricultural practices affecting SOM stocks was presented by Dignac et al. (2017). More in detail, both the statistical and geostatistical analyses demonstrated as the samples collected in field managed according to CA have higher SOM content as compared to those collected in OR and CO fields. However, taking into account the great influence of soil type on SOM content which came to light in the investigated area, we carried out a further analysis to exclude that differences between farming systems can be distorted by different frequencies of soil types. Observing the frequency of the two SOM-richest soil types (orthic Luvisols and calcic Cambisols) for each farming type, we noticed how there are no OR sample collected in Calcic Cambisols (Fig. 8). This unbalanced distribution could affect the SOM comparison between farming types, however carrying out a test excluding all the Calcic Cambisols samples, we observed how CA still showed an average SOM content (3.26 %) significantly higher than OR (2.91 %) and CO (2.73 %).

When we consider the duration of adoption of CA and OR practices, it becomes evident that CA, when implemented for more than 3 years, exerts a significant impact on SOM, even surpassing the effect of OR practices adopted for more than 5 years. Furthermore, the greater variability observed in CA (Table2; Fig. 5), as opposed to both OR and CO ones, and with OR variability higher than CO, aligns with the dynamics of converting from CO to alternative farming approaches. This pattern is influenced by the diverse conversion histories and durations represented in our dataset, which encompasses a wide range of farms undergoing various stages of conversion. These findings agree, to some extent, with previous literature as reported by Perego et al. (2019), who studied a smaller number of farms within the same study area, comparing conservation practices to conventional practices. Perego et al. (2019) demonstrated that conservation agriculture led to a notably higher SOC content within the medium-term group, where "medium--term" denotes a period exceeding 3 years but less than 10 years (from 2006 to 2013, with soil analyses conducted between 2014 and 2016). According to our results, one of the more effective practices for SOM conservation is no-tillage and this is in agreement with the findings of Perego et al. (2019) and Tabaglio et al. (2009) which observed a higher SOC increase for no-tillage fields as compared to conventional tillage.

Our findings and the map of Δ SOCc provided by De Rosa et al. (2023) show that the ideal conditions for SOM accumulation in the first soil layer within Po basin are more likely to occur in Cambisols, in particular in Eutric Cambisols, thus along the main stem of the Po river and in the Northern -East part of the basin and close to the delta on Fluvisols. Even though the average rate of Δ SOCc was generally quite low, the standard deviation of the Δ SOCc values is generally very high; consequently it might be assumed that the adoption of the more tailored farming practices could push the rate beyond the maximum observed values, i.e. beyond +0.36 g C kg^{-1} $year^{-1}$. Dal Ferro et al. (2020) analyzed SOC along soil profiles (i.e., topsoil and subsoil) of a 50 years old experiment in northeast Italy observing as the total SOC stock noticeably changes according soil types; in silty loam soil they detected a SOC stock of 116.6 Mg ha^{-1}, while in sandy Arenosol the SOC stock was 23.2 Mg ha^{-1}. Generally the SOC ratio between topsoil (20 cm) and full profile can vary between 0.26 and 0.56 (Jobbagy and Jackson, 2000; Omonode and Vyn, 2006), and Dal Ferro et al. (2020) concluded that topsoil SOC accumulation could be an affordable proxy for SOC storage estimation in subsoil. However topsoil texture and soil management strongly influences the differences in terms of SOC accumulation between topsoil and subsoil, for instance, SOC is generally more labile in sandy soils that leads to a very low topsoil/subsoil SOC ratio (Dal Ferro et al., 2020).

Regarding the farming practices, the results of the statistical and geostatistical analysis show that although characterized by great variability in the expected values of SOM in each plot (Fig. 5a), the most influential practices for increasing SOM in the Po basins are those related to conservation agriculture and in particular no-tillage in combination with organic fertilization and including fodder crops in the rotation. These findings are in agreement with those of Dal Ferro et al. (2020) that indicated the combination of minimum soil disturbance and organic inputs as the best management practices in croplands for increasing SOC accumulation, especially in soil poor in SOC, i.e. soils far from the SOC stock saturation. The adoption of these practices for at least 3 years in Eutric Cambisols and Eutric Fluvisols could help to reach noticeable results in terms of SOM increasing rate that we can estimate between 0.2 % and 0.4 %. Obviously the magnitude of the SOM increase is related to the initial SOM content and to the clay content, maximum increase are then expected where we have low initial SOM content and high clay (De Rosa et al., 2023), while low rates can be envisaged where SOM is close to its saturation and clay content is low. The other soil types insisting in the Po basin still offer prospects of improvements where the above described practices will be adopted. A further support of what was stated above about CA practices, the standard deviation of estimation associated at each SOM expected value is the lowest for CA (Fig. 5b) and this might be interpreted as the occurrence of the lowest variability of SOM values locally for CA, that would provide clear evidence of less variability within individual plots submitted to CA compared to CO and OR farming.

All these findings suggest the adoption of soil management tailored to the real potential of the region of interest in terms of SOC stock. The results of this study provide essential information for supporting agriculture towards an effective increasing of the soil fertility and health. As De Rosa et al. (2023) suggested, carbon farming policies should not be limited to the SOC quantification, but it should consider the different soil potentialities existing in Europe, because soil types and climate, both precipitation and temperature, strongly influence the changes in SOC content in croplands. Consequently, we cannot expect the same yearly SOC change rate in Mediterranean and Continental European regions, due to very different rates of SOM mineralization; but even in the same climate region, the different substrates can generate different soil textures in topsoil and we need to consider how loamy and clay soils are naturally more rich than sandy soils due to higher aggregate stability and water retention capability. In this regard, Perego et al. (2019) suggested a reinforcement of the policy support at farm and regional scale for improving conservation agriculture techniques making them more adaptable to local realities. Spatial information, such those provided in this study, could facilitate the delineation of tailored solutions for each European Member State for targeting future actions related to carbon farming and to achieve compliance with the LULUCF regulation (De Rosa et al., 2023). Also moving in this direction is the recent EU Directive Soil Monitoring and Resilience and the outlook outlined in the report on the Status of health in the European soils about soil organic carbon change. Moreover, in this report is emphasized the importance of creating an awareness among farmers of the current situation about the unsustainable use of agricultural land and to promote a more sustainable use of agricultural soils, which might increase the SOM stock.

5. Conclusions

A novel geospatial approach has been implemented for evaluating how farming systems influence organic matter content in cropland soils. The results provided clear evidences of the spatial correlation between SOM and farming system and soil type in the Po river basin, a pivotal Italian agriculture area. The spatial and statistical analyses showed a significant higher SOM content in field managed according conservation agriculture practices as compared to other farming systems. The findings from the current study offer crucial insights to support advancements in agriculture for enhancing soil fertility and health. Simultaneously, they underscore the importance of extensive research aimed at developing and customizing diverse farming approaches on both regional and farm scales. At these levels, there is a clear imperative for sustained, interdisciplinary investigations to discern whether conservation practices, in comparison to other farming systems, can unlock social and economic advantages while fostering resilience against the impacts of climate change for the Mediterranean hotspot.

In conclusion, the application of established knowledge is pivotal not only for persuading farmers to transition to alternative farming practices but also for equipping them with the necessary knowledge, tools, and information. This holistic understanding is essential for fostering sustainable agricultural practices and ensuring a resilient and productive agricultural sector in the face of evolving environmental challenges.

Funding

This study was partially supported by the SOC research project DBA. AD001.503 funded by Barilla G. e R. Fratelli S.p.A.,.

CRediT authorship contribution statement

Flavio Bertinaria: Writing – review & editing, Writing – original draft, Resources, Project administration, Funding acquisition, Data curation. **Piero Toscano:** Writing – review & editing, Writing – original draft, Validation, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Fabio Castaldi:** Writing – review & editing, Writing – original draft, Visualization, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Gabriele Buttafuoco:** Writing – original draft, Methodology, Investigation, Formal analysis, Data curation.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Fabio Castaldi reports financial support was provided by Barilla G. e R. Brothers. Piero Toscano reports financial support was provided by Barilla G. e R. Brothers. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

References

Armstrong, M., 1998. Basic linear geostatistics. Basic Linear Geostat. https://doi.org/10.1007/978-3-642-58727-6.

Awale, R., Chatterjee, A., Franzen, D., 2013. Tillage and N-fertilizer influences on selected organic carbon fractions in a North Dakota silty clay soil. Soil Tillage Res. 134, 213–222. https://doi.org/10.1016/J.STILL.2013.08.006.

Babu, S., Singh, R., Avasthe, R., Kumar, S., Rathore, S.S., Singh, V.K., Ansari, M.A., Valente, D., Petrosillo, I., 2023. Soil carbon dynamics under organic farming: impact of tillage and cropping diversity. Ecol. Indic. 147, 109940 https://doi.org/10.1016/J.ECOLIND.2023.109940.

Beck, H.E., Zimmermann, N.E., McVicar, T.R., Vergopolan, N., Berg, A., Wood, E.F., 2018. Present and future Köppen-Geiger climate classification maps at 1-km resolution. Sci. Data 5, 1–12. https://doi.org/10.1038/sdata.2018.214.

Beniston, M., 2005. Mountain climates and climatic change: an overview of processes focusing on the European Alps. Pure Appl. Geophys 162, 1587–1606. https://doi.org/10.1007/S00024-005-2684-9/METRICS.

Bleines, C., Deraisme, J., Geffroy, F., Jeannée, N., Perseval, S., Rambert, F., 2018. Isatis technical references (No. 2018.5). Geovariances, Avon Cedex.

de Brogniez, D., Ballabio, C., Stevens, A., Jones, R.J.A., Montanarella, L., van Wesemael, B., 2015. A map of the topsoil organic carbon content of Europe generated by a generalized additive model. Eur. J. Soil Sci. 66, 121–134. https://doi.org/10.1111/EJSS.12193.

Buttafuoco, G., Castrignanò, A., Cucci, G., Lacolla, G., Lucà, F., 2017. Geostatistical modelling of within-field soil and yield variability for management zones delineation: a case study in a durum wheat field. Precis. Agric. 18, 37–58. https://doi.org/10.1007/S11119-016-9462-9/METRICS.

Calvo de Anta, R., Luís, E., Febrero-Bande, M., Galiñanes, J., Macías, F., Ortíz, R., Casás, F., 2020. Soil organic carbon in peninsular Spain: influence of environmental factors and spatial distribution. Geoderma 370, 114365. https://doi.org/10.1016/J.GEODERMA.2020.114365.

Carsten, P., Bartkowski, B., Dönmez, C., Don, A., Mayer, S., Steffens, M., Weigl, S., Wiesmeier, M., Wolf, A., Helming, K., 2023. Carbon farming: are soil carbon certificates a suitable tool for climate change mitigation? J. Environ. Manag. 330, 117142 https://doi.org/10.1016/J.JENVMAN.2022.117142.

Chawla, N.V., Bowyer, K.W., Hall, L.O., Kegelmeyer, W.P., 2011. SMOTE: synthetic minority over-sampling technique. J. Artif. Intell. Res. 16, 321–357. https://doi.org/10.1613/jair.953.

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 Tillage Res 188, 41–52. https://doi.org/10.1016/J.STILL.2018.04.011.

Chilès, J.P., Delfiner, P., 2012. Geostatistics: modeling spatial uncertainty: Second Edition. Geostatistics: Modeling Spatial Uncertainty: Second Edition 1–699. https://doi.org/10.1002/9781118136188.

Dal Ferro, N., Piccoli, I., Berti, A., Polese, R., Morari, F., 2020. Organic carbon storage potential in deep agricultural soil layers: Evidence from long-term experiments in northeast Italy. Agric. Ecosyst. Environ. 300, 106967 https://doi.org/10.1016/J.AGEE.2020.106967.

De Rosa, D., Ballabio, C., Lugato, E., Fasiolo, M., Jones, A., Panagos, P., 2023. Soil organic carbon stocks in European croplands and grasslands: How much have we lost in the past decade? Glob. Chang Biol., e16992 https://doi.org/10.1111/GCB.16992.

Dignac, M.F., Derrien, D., Barré, P., Barot, S., Cécillon, L., Chenu, C., Chevallier, T., Freschet, G.T., Garnier, P., Guenet, B., Hedde, M., Klumpp, K., Lashermes, G., Maron, P.A., Nunan, N., Roumet, C., Basile-Doelsch, I., 2017. Increasing soil carbon storage: mechanisms, effects of agricultural practices and proxies. A review. Agron. Sustain. Dev. 37, 1–27. https://doi.org/10.1007/S13593-017-0421-2.

Dupla, X., Lemaître, T., Grand, S., Gondret, K., Charles, R., Verrecchia, E., Boivin, P., 2022. On-farm relationships between agricultural practices and annual changes in organic carbon content at a regional scale. Front. Environ. Sci. 10, 834055 https://doi.org/10.3389/FENVS.2022.834055/BIBTEX.

EIP-AGRI Focus Group Soil Organic Matter in Mediterranean regions, 2015 ⟨https://ec.europa.eu/eip/agriculture/sites/default/files/eip-agri_fg_soil_organic_matter_final_report_2015_en_0.pdf⟩. Accessed 7 Sept 2023.

EU SOIL OBSERVATORY -EUSO Soil Health Dashboard ⟨https://esdac.jrc.ec.europa.eu/esdacviewer/euso-dashboard/#close⟩). Accessed 4 Sept 2023.

Eurostat: Technical reference document C-3: Classification (Land cover & Land use), 2015 - ⟨https://ec.europa.eu/eurostat/documents/205002/6786255/LUCAS2015-C3-Classification-20150227.pdf/969ca853-e325-48b3-9d59-7e86023b2b27⟩. Accessed 4 Sept 2023.

Falloon, P., Betts, R., 2010. Climate impacts on European agriculture and water management in the context of adaptation and mitigation—the importance of an integrated approach. Sci. Total Environ. 408, 5667–5687. https://doi.org/10.1016/J.SCITOTENV.2009.05.002.

Fernandez, U.O., Scarpa, S., Orgiazzi, A., Panagos, P., Van, L.M., Maréchal, A., Jones, A., 2022. LUCAS 2018 Soil Module 128. https://doi.org/10.2760/215013.

Gattinger, A., Muller, A., Haeni, M., Skinner, C., Fliessbach, A., Buchmann, N., Mäder, P., Stolze, M., Smith, P., Scialabba, N.E.H., Niggli, U., 2012. Enhanced top soil carbon stocks under organic farming. Proc. Natl. Acad. Sci. USA 109, 18226–18231. https://doi.org/10.1073/PNAS.1209429109/SUPPL_FILE/SD01.XLSX.

Geoportale del distretto Po, ⟨https://webgis.adbpo.it/⟩ Accessed 7 Sept 2023.

González-Sánchez, E.J., Ordóñez-Fernández, R., Carbonell-Bojollo, R., Veroz-González, O., Gil-Ribes, J.A., 2012. Meta-analysis on atmospheric carbon capture in Spain through the use of conservation agriculture. Soil Tillage Res 122, 52–60. https://doi.org/10.1016/J.STILL.2012.03.001.

Govaerts, B., Verhulst, N., Castellanos-Navarrete, A., Sayre, K.D., Dixon, J., Dendooven, L., 2009. Conservation agriculture and soil carbon sequestration: between myth and farmer reality. Crit. Rev. Plant Sci. 28, 97–122. https://doi.org/10.1080/07352680902776358.

Greenland, D.J., Rimmer, D., Payne, D., 1975. Determination of the structural stability class of english and welsh soils, using a water coherence test. J. Soil Sci. 26, 294–303. https://doi.org/10.1111/J.1365-2389.1975.TB01953.X.

Guo, Z., Han, J., Li, J., Xu, Y., Wang, X., 2019. Effects of long-term fertilization on soil organic carbon mineralization and microbial community structure. PLOS One 14, e0211163. https://doi.org/10.1371/JOURNAL.PONE.0211163.

IPCC, 2019. Climate Change and Land: an IPCC Special Report on Climate Change, Desertification, Land Degradation, Sustainable Land Management, Food Security, and Greenhouse Gas Fluxes in Terrestrial Ecosystems. Cambridge University Press, Cambridge, UK and New York, NY, USA, p. 896. https://doi.org/10.1017/9781009157988.

IUSS Working Group W.R.B., 2015. World Reference Base for Soil Resources 2014, Update 2015. International Soil Classification System for Naming Soils and Creating Legends for Soil Maps. World Soil Resources Reports No. 106, Rome: FAO.

Jobbagy, 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. https://doi.org/10.2307/2641104.

Jones, R.J.A., Hiederer, R., Rusco, E., Montanarella, L., 2005. Estimating organic carbon in the soils of Europe for policy support. Eur. J. Soil Sci. 56, 655–671. https://doi.org/10.1111/J.1365-2389.2005.00728.X.

Liliana, V.J., Gutierrez Boem, F., Garcia, F., Rubio, G., 2020. Long-term fertilization does not affect soil carbon/nitrogen/sulfur ratios or the proportion between labile and nonlabile fractions in Mollisols. Soil Sci. Soc. Am. J. 84, 798–810. https://doi.org/10.1002/SAJ2.20058.

Loveland, P., Webb, J., 2003. Is there a critical level of organic matter in the agricultural soils of temperate regions: a review. Soil Tillage Res. 70, 1–18. https://doi.org/10.1016/S0167-1987(02)00139-3.

Meersmans, J., Van Wesemael, B., Van Molle, M., 2009. Determining soil organic carbon for agricultural soils: a comparison between the Walkley & Black and the dry combustion methods (north Belgium). Soil Use Manag. 25, 346–353. https://doi.org/10.1111/J.1475-2743.2009.00242.X.

Morais, T.G., Teixeira, R.F.M., Domingos, T., 2019. Detailed global modelling of soil organic carbon in cropland, grassland and forest soils. PLOS One 14. https://doi.org/10.1371/JOURNAL.PONE.0222604.

Munoz-Rojas, M., Jordan, 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, 375–386. https://doi.org/10.5194/SE-3-375-2012.

Newton, P., Civita, N., Frankel-Goldwater, L., Bartel, K., Johns, C., 2020. What is regenerative agriculture? A review of scholar and practitioner definitions based on processes and outcomes. Front. Sustain. Food Syst. 4, 577723 https://doi.org/10.3389/FSUFS.2020.577723/BIBTEX.

Ogle, S.M., Swan, A., Paustian, K., 2012. No-till management impacts on crop productivity, carbon input and soil carbon sequestration. Agric. Ecosyst. Environ. 149, 37–49. https://doi.org/10.1016/J.AGEE.2011.12.010.

Omonode, R.A., Vyn, T.J., 2006. Vertical distribution of soil organic carbon and nitrogen under warm-season native grasses relative to croplands in west-central Indiana, USA. Agric., Ecosyst. Environ. 117 (2–3), 159–170. https://doi.org/10.1016/J.AGEE.2006.03.031.

Palm, C., Blanco-Canqui, H., DeClerck, F., Gatere, L., Grace, P., 2014. Conservation agriculture and ecosystem services: an overview. Agric. Ecosyst. Environ. 187, 87–105. https://doi.org/10.1016/J.AGEE.2013.10.010.

Panagos, P., van Liedekerke, M., Jones, A., Montanarella, L., 2012. European Soil Data Centre: Response to European policy support and public data requirements. Land Use Policy 29 (2), 329–338. https://doi.org/10.1016/J.LANDUSEPOL.2011.07.003.

Perego, A., Giussani, A., Sanna, M., Fumagalli, M., Carozzi, M., Alfieri, L., Brenna, S., Acutis, M., 2014. The ARMOSA simulation crop model: overall features, calibration and validation results. Ital. J. Agrometeorol. 18, 23–38.

Perego, A., Rocca, A., Cattivelli, V., Tabaglio, V., Fiorini, A., Barbieri, S., Schillaci, C., Chiodini, M.E., Brenna, S., Acutis, M., 2019. Agro-environmental aspects of conservation agriculture compared to conventional systems: a 3-year experience on 20 farms in the Po valley (Northern Italy). Agric. Syst. 168, 73–87. https://doi.org/10.1016/J.AGSY.2018.10.008.

R Core Team, 2022. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria.URL ⟨https://www.R-project.org/⟩.

Sabelli, C., 2023. Examining the role of climate change in the Emilia-Romagna floods. Nature. https://doi.org/10.1038/D43978-023-00082-Z.
Sanaullah, M., Usman, M., Wakeel, A., Cheema, S.A., Ashraf, I., Farooq, M., 2020. Terrestrial ecosystem functioning affected by agricultural management systems: a review. Soil Tillage Res. 196, 104464 https://doi.org/10.1016/J.STILL.2019.104464.
Sanderman, J., Hengl, T., Fiske, G.J., 2017. Soil carbon debt of 12,000 years of human land use. Proc. Natl. Acad. Sci. USA 114, 9575–9580. https://doi.org/10.1073/PNAS.1706103114/SUPPL_FILE/PNAS.1706103114.SAPP.PDF.
Sanford, G.R., Posner, J.L., Jackson, R.D., Kucharik, C.J., Hedtcke, J.L., Lin, T.L., 2012. Soil carbon lost from Mollisols of the North Central U.S.A. with 20 years of agricultural best management practices. Agric. Ecosyst. Environ. 162, 68–76. https://doi.org/10.1016/J.AGEE.2012.08.011.
Schillaci, C., Saia, S., Lipani, A., Perego, A., Zaccone, C., Acutis, M., 2021. Validating the regional estimates of changes in soil organic carbon by using the data from paired-sites: the case study of Mediterranean arable lands. Carbon Balance and Management 16 (1), 1–15. https://doi.org/10.1186/S13021-021-00182-7/TABLES/7.
Scoones, I., Stirling, A., Abrol, D., Atela, J., Charli-Joseph, L., Eakin, H., Ely, A., Olsson, P., Pereira, L., Priya, R., van Zwanenberg, P., Yang, L., 2020. Transformations to sustainability: combining structural, systemic and enabling approaches. Curr. Opin. Environ. Sustain. 42, 65–75. https://doi.org/10.1016/J.COSUST.2019.12.004.
Stavi, I., Bel, G., Zaady, E., 2016. Soil functions and ecosystem services in conventional, conservation, and integrated agricultural systems. A review. Agron. Sustain Dev. 36, 1–12. https://doi.org/10.1007/S13593-016-0368-8/TABLES/1.
Syswerda, S.P., Corbin, A.T., Mokma, D.L., Kravchenko, A.N., Robertson, G.P., 2011. Agricultural management and soil carbon storage in surface vs. deep layers. Soil Sci. Soc. Am. J. 75, 92–101. https://doi.org/10.2136/SSSAJ2009.0414.
Tabaglio, V., Gavazzi, C., Menta, C., 2009. Physico-chemical indicators and microarthropod communities as influenced by no-till, conventional tillage and nitrogen fertilisation after four years of continuous maize. Soil Tillage Res. 105, 135–142. https://doi.org/10.1016/J.STILL.2009.06.006.
Virto, I., Barré, P., Burlot, A., Chenu, C., 2012. Carbon input differences as the main factor explaining the variability in soil organic C storage in no-tilled compared to inversion tilled agrosystems. Biogeochemistry 108, 17–26. https://doi.org/10.1007/S10533-011-9600-4/METRICS.
Wackernagel, H., 2003. Multivariate geostatistics. Multivar. Geostat. https://doi.org/10.1007/978-3-662-05294-5.
Webster, R., Oliver, M.A., 2008. Geostatistics for Environmental Scientists: Second Edition. Geostatistics for Environmental Scientists: Second Edition 1–315. https://doi.org/10.1002/9780470517277.
Wu, H., Kida, M., Domoto, A., Hara, M., Ashida, H., Suzuki, T., Fujitake, N., 2019. The effects of fertilization treatments and cropping systems on long-term dynamics and spectroscopic characteristics of dissolved organic matter in paddy soil. Soil Sci. Plant Nutr. 65, 557–565. https://doi.org/10.1080/00380768.2019.1689794.
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. https://doi.org/10.1016/J.SCITOTENV.2016.03.085.
Zheng, F., Liu, X., Ding, W., Song, X., Li, S., Wu, X., 2023. Positive effects of crop rotation on soil aggregation and associated organic carbon are mainly controlled by climate and initial soil carbon content: a meta-analysis. Agric. Ecosyst. Environ. 355, 108600 https://doi.org/10.1016/J.AGEE.2023.108600.