CARBON 4 SOIL QUALITY

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ADAPTATION OF ORGANIC CARBON ANALYSIS STANDARDS AND MONITORING PROCEDURES

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1 INTRODUCTION

Carbon sequestration is crucial for the effective removal of greenhouse gas emissions and can thereby have substantial effects on the atmosphere and climate change.

Smith et al (2020) state that there is an increasing global interest in improving soil management in order to increase soil organic carbon levels, promote climate change mitigation, strengthen resistance to climate change, and support food security.

The composition of soil organic matter affects soil functions and characteristics. Soil organic carbon plays a crucial role in the overall behavior of soils and agro-ecosystems. It supplies energy for soil microorganisms, stores and supplies nutrients (nitrogen, phosphorus, and potassium) for plant growth, enhances soil structure, and contributes to the soil's capacity to retain water and resist erosion.

Schillaci (2018) states that Mediterranean regions have faced significant human pressures, such as fires, intense land cultivation, and other forms of inadequate management. The phenomena have resulted in detrimental effects on both natural and agricultural ecosystems, leading to significant land degradation through desertification, soil erosion, landslides, and declining SOC levels. (Saia et al. 2017; Persichillo et al. 2017)

This deliverable contributes to WP2 where a solid base for future testing of carbon farming in the Euro-MED area will be prepared through elaboration of a feasible action plan, training material, improved visibility and policy connections for future cooperation. The objective of the deliverable is to propose standards to properly assess SOM content and soil quality. Specific objectives are:

- Selection of indicators to assess soil functioning, standardization of reference values of soil indicators and selection of a Minimum Data Set.
- Propose carbon sequestration models adapted for MED agriculture.
- Propose standardization of soil sampling schemes and build consistent soil quality related databases and references
- Propose analytical determination of organic carbon in soil and simple on-field procedures to self-check soil quality at the farm level.
- Propose a SOM monitoring methodology including possibility to use novel Near-Infrared Reflectance Spectroscopy or colorimetry-based techniques.
- Evaluate the impact of agricultural practices, Soil Improving Cropping Systems, and climate crisis on crop production and carbon sequestration.

The deliverable is structured in five chapter as follows:

Chapter 1. Introduction, presenting the general scope of the deliverable.

Chapter 2. Monitoring of SOM, in which the methods for measuring SOM are presented.

Chapter 3. Monitoring of Soil Quality, in which an extensive analysis on soil quality monitoring and soil quality quantification is described.

Chapter 4. Soil carbon sequestration models, where a review of existing approaches and models is presented, including applications of selected models.

Chapter 5. Consistent soil quality related databases and references, in which existing global, European and national databases of soil quality indicators are presented.

Chapter 6. Conclusions.

1.1 References

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Saia S., Schillaci C., Lipani A., Fantappiè M., Märker M., Lombardo L., Matranga M.G., Ferraro V., Guaitoli F. & Acutis M. (2017) - Protection of soil from the loss of organic carbon by considering erosion and managing land use at varying soil type: indication from a model semiarid area. In: Global Symposium on Soil Organic Carbon. Rome, Italy, pp. 510-515.

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2 MONITORING OF SOM

2.1 Introduction

Soil organic matter, a complex, dynamic component of terrestrial ecosystem, is a core indicator of soil quality. Carbon is the prime element present in SOM, comprising 48%-58% of the total weight. Rapid and precise measurement of soil organic carbon is essential to monitor temporal changes in SOM content. Since total C is the sum of both organic and inorganic C pools, several methods have been developed or modified over the years to determine SOC. A brief description of the measurement, principles, merits and limitations of the commonly used methods for measurement of SOC is discussed.

2.2 Soil sampling

2.2.1 SOIL SURVEY

Soil survey is a complex process that depends on proper specification and sound planning. An important part of the soil survey is the selection of the most suitable sampling scheme which should be aligned with the general and specific purpose of the field survey, prior knowledge of the region, scale, and the surveyor experience.

McKenzie et al. (2008) refer to two general types of field surveys: qualitative and quantitative methods of survey. Qualitative methods include a) an integrated survey, that relies on the assumption of interdependency of land characteristics and their correlation with environmental features and is intended primarily to identify the soils and vegetation within the targeted areas, b) free surveys, which are the conventional form of soil survey while the c) the stratigraphic survey, which places emphasis on the soil mantle rather than the soil profile. The soil materials approach is a hybrid type of soil survey that descriptions and definitions of soil materials are based on their morphology, without considering their position in the soil profile. Qualitative grid survey is a method where field survey is based on a regular grid.

Quantitative soil survey includes the analysis of soil behavior and land attributes considering the quantitative inputs and outputs by using empirical and process models across different ranges and scales. Commonly used quantitative methods are based on geostatistical approaches, where maps are produced as grid estimates based on field data. Another set of statistical quantitative methods are correlation, regression, collectively known as environmental correlation (e.g. SCORPAN, McBratney et al 2003).

2.2.2 APPROACHES AND STRATEGIES IN SOIL SAMPLING

Soil forms a nearly continuous mantle whose properties and characteristics change continuously in space. Only a few soil properties can be observed from the soil surface, so the soil properties must be observed through the excavation of soil profiles or by soil sampling at a certain depth.

Sampling is the process of choosing a subset of samples to measure from the entire population. The measurements taken on this subset, or sample, are subsequently used to estimate the parameters, or attributes, of the entire population. There is no naturally defined volume of quantity to be used as a representative sample. Choosing the most effective technique for selecting the samples that will finally be used to estimate the population's attributes is known as sampling design. (Carter and Gregoric 2008).

Choosing the right time and place to take the soil sample and how to collect the samples are the main questions that significantly influence the survey`s success and usefulness, which is primarily determined by the purpose of investigation and logistic constraints. A good strategy for planning the scheme is to start at the end and reason backward (de Gruijter, 2000). In the case of the LUCAS survey program, sampling points with similar densities were allocated for each country, rather than allocating sampling points according to soil heterogeneity. Random distribution of the sampling locations is an approach often used for monitoring scheme inventories, while the second approach when soil heterogeneity is the primary criterion, is used for systematic soil surveys for mapping purposes.

Sampling locations can be chosen following a system of a) *haphazard sampling* when sampling locations are selected with no preferences or criteria, b*) judgment sampling*, in which the researcher locates sapling sites by using his judgment and is usually used in pedogenetic and soil geomorphic studies aiming to identify the mechanisms responsible for the development of soil characteristics, and c) *probability sampling* (Carter and Gregoric 2008). Similarly, Gruijter (2006) proposes three possible modes of sample point selections: convenience method which is similar to the haphazard sampling method where sampling locations are selected on the most convenient locations for the surveyor, purposive sampling when the surveyor tries to locate the sample points based on a given purpose, like in the case of mapping soil classes, whereby the surveyor identifies the sample points in locations that are anticipated to provide the most valuable information regarding the classification of soil; and the third mode of sampling locations, which is known as probability sampling, where, unlike the other modes, the sample points are selected at random location.

Generating a sample that is representative of the target population is the primary objective of sampling. The only sure way of avoiding bias inherent in purposive sampling is by using probabilistic sampling. If the selection of samples is not probabilistic, there is a high risk that the sample will not accurately represent the entire population. (McKenzie at al. 2008).

In soil and earth sciences, there are multiple choices available for creating a suitable sample plan. However, the most generally utilized methods are random and systematic sampling. Gruijter (2006) distinguishes two groups of sampling approaches: the design-based approach used in classical soil survey sampling and the model-based approach, used in geostatistics.

In the case of the design-based approach, the locations are random while the population is fixed. The design-based approach assesses uncertainty by iteratively sampling with various sets of sample sites, treating the pattern of values in the area as unknown but constant. The model-based approach assesses uncertainty by iteratively sampling from a predetermined set of sample points and is recommended in cases when the spatial structure of soil variation in a certain region is the scope of interest, (Brus and de Gruijter 1997; de Gruijter, 2006). It should be noted that although probabilistic sampling avoids bias, it can be rather expensive.

2.2.3 SAMPLING DESIGNS

2.2.3.1 *Simple random sampling*

In simple random sampling, it is equally probable that all samples of the defined size will be selected independently of one another. Apart from a fixed sample size that was previously determined, there are no other constraints. Initially, the minimum and maximum X and Y coordinates of the area are determined. For each sampling point, two independent random X and Y coordinates are generated from the pool of X and Y min and max intervals, and a point-to-polygon routine is used to determine whether the point falls within the area.

2.2.3.2 *Stratified Sampling*

In a stratified sampling design, the area is divided into relatively homogeneous sub-regions called strata, and this design is based on site-specific information extracted from EO data, thematic maps like soil maps or land cover maps, using spatial pattern detection techniques. Each stratum is then sampled independently from each other by applying a simple random sampling design. The methods for selecting sampling points explained in the simple random sampling section are applied separately for each stratum.

2.2.3.3 *Two-Stage Sampling*

In two-stage sampling, the areas are subdivided into subareas, but the sampling is limited to a specific number of randomly chosen subareas called primary units. Sampling points within the selected strata are identified as explained in simple random sampling section. This approach is used in large-scale surveys and is usually referred to as multistage sampling.

2.2.3.4 Cluster sampling

Cluster sampling involves the selection of predetermined groups of points, rather than selecting individual points. The number of clusters that can be created is indefinite, so only selected sets of clusters are sampled. The algorithm for cluster creation starts with the selection of a random point according to the rules of simple random sampling. The other points of the cluster are created following predetermined geometric rules (e.g. prechosen distance in both directions).

2.2.3.5 Systematic sampling

Systematic sampling involves randomly selecting points from a predetermined set, unlike the simple, stratified and two-stage random sampling methods. In this method, unlike cluster sampling, only one cluster is selected, so this can be considered as a special case of cluster sampling. The cluster should be defined to cover the area as well as possible, which is usually achieved by creating a cluster as a grid with a triangular, hexagonal, or square shape.

The complex nature of landforms at the location of interest is also a factor to be considered. Either a transect or a grid can be utilized for level and near-level locations (Carter and Gregoric, 2008). The suitability of transects on sloping terrain is partially determined by the plan (across-slope) curvature. However, if there is significant plan curvature, one transects alone will not be adequate. In this scenario, a zigzag pattern or numerous, randomly positioned transects could be employed, although a grid pattern is more commonly utilized.

2.2.4 ADVANCED DESIGN-BASED STRATEGIES

2.2.4.1 Compound sampling

Compound Sampling is a combination of the previous basic strategies. One example of compound strategy is a combination of a two-stage sampling method with systematic sampling, instead of using the simple random sampling method as previously explained. In this case, a square grid of 2x2 primary units is selected from the previously established grid of the area, and then a 2 × 2 square grid is applied within each primary unit.

2.2.4.2 Spatial Systematic Strategies

This is another group of advanced design strategies. The region is predominantly partitioned into square strata, with one specific point being chosen for each stratum, although not in an independent manner. A random X position or coordinate is generated for every row of strata, while a random Y coordinate is generated for every column. The sample point inside a stratum is determined by merging the row and column coordinates.

2.2.5 REFERENT SOIL SAMPLING GUIDES AND APPROACHES

The USDA Field Book for Describing and Sampling Soils (2021) states that the usefulness of soil property data is limited without context, as it depends on a geo-referenced description to be meaningful. The Field Book emphasizes the need to stratify soil areas by similar geologic and pedogenetic processes, followed by random sampling within the stratified areas, which is at the core of the sampling methodology.

The JRC`s "Soil Sampling Protocol to Certify the Changes of Organic Carbon Stock in Mineral Soil of the European Union" (Stolbovoy et al 2007) defines a method for identifying the changes of SOC in mineral soil, referred to as Area-Frame Randomized Soil Sampling (AFRSS). The geolocation of each sampling location with sampling sites and position of the soil profile should be identified by GPS to enable revisiting of the sample sites. For the determination of bulk density, the JRC Sampling protocol recommends the method of using an undisturbed sample with a minimum volume of 100 cm^3 taken from non-stony soils.

According to the LUCAS methodology (Toth, G. et al, 2014), the best soil mapping is performed when a design-based, multi-stage stratified random sampling approach is chosen (McKenzie et al, 2008). The CORINE LANDCOVER 2000 dataset, with a resolution of 100 meters, is utilized to determine the corresponding area of each land use category. The quantity of selected points is directly related to the proportion of land use coverage in each country. The quantiles of each landform and land use class are combined, mapped and transformed into vectors to calculate the unique value of the strata in each location. After the finalization of the process of stratification, soil sampling locations were selected.

2.2.6 FIELD MEASUREMENT

Soil properties are measured and described in various units and categories expressed on scale or ordered according to certain criteria. In general soil attributes are expressed as nominal values (as a binary or multistate value), ordinal values that can be ordered or ranked as discrete classes, interval attributes expressed on a continuous scale and which do not contain true zero (pH, air temperatures), and ratio scale attributes.

2.2.7 SITE DESCRIPTION

During the field survey and collection of soil specimens for SOC measurement, it is of particular interest to record data for the site specifics like land use (actual and historical data), records for the litter and woody debris, that can be used for estimating total carbon density and procedures for sampling the site-carbon in coarse woody debris, surface litter and roots (McKenzie et al 2008). Data related to management practices, soil cultivation system, cropping patterns and inputs, especially of organic materials, should also be recorded.

2.2.8 SOIL SAMPLING/SPECIMEN COLLECTION

This is the next step after the adoption of the most appropriate soil sampling strategy and sample design. Depending on the purpose of the field soil survey and soil attributes that are surveyed several approaches of the collection of samples are recommended according to McKenzie et al (2008), a common practice is to collect specimens spanning throughout the entire depth of the soil profile. Another method is to collect specimens from the centers of predefined sampling intervals, and the third recommended approach is the subdivision of soil profile into horizons. In such cases, when the soil profile is subdivided into soil horizons, samples are collected continuously throughout the entire depth of the soil horizon as disturbed specimens.

In the case of interval sampling of disturbed specimens, the recommendation is to use a maximum sampling depth up to 10 cm, for the first 30 cm, and on 30 cm intervals for the depth from 30-100 cm. In some special cases of soil monitoring (heavy metals contents, acidification etc.) the first layer may need to be sampled up to 5 cm. depth. Below 2 m, the sampling interval should be sufficient to characterize the material found. If the measurement of organic matter and/or pH is significant, it is recommended to collect a sample from a depth of 0-15 cm (Carter and Gregoric, 2008).

The LUCAS sampling procedure recommends collecting samples from the designated locations by a process of composite sampling (bulk sampling). According to this methodology, five soil sub-samples must be collected from each sampling site and a mixture of these soil samples should be transported to the laboratory. Soil samples from the central and the four sub-sampling locations must be placed together in a plastic container and mixed in order to prepare the required composite sample. The quantity of soil needed from the composite sample is about 500 grams. The fundamental concept of this methodology is that the soil sample should sufficiently represent the area defined by the chosen points.

2.2.9 UNDISTURBED/CORE SOIL SAMPLE COLLECTION

Some procedures involve the preservation of the natural structure of the soil. Physical measurements usually require the acquisition of intact samples, while chemical analyses are generally conducted on altered samples.

Several soil sample procedures can be used to evaluate coarse fragments and bulk density, including the clod, core, pit, or excavation approach. The fundamental principle is to extract a sample that is larger than the largest rock within the sample. The level of soil structure development, soil water content, and potential distortion during sampling will impact the size of the sample and the caution required during handling.

2.2.10 BULK DENSITY

Soil bulk density (ρ_b) is the ratio of the mass (g) of an oven-dry soil sample to the volume (cm) of that sample at a specified moisture condition (Sheldrick B.H. 1984). Multiple duplicate samples are required to obtain an accurate estimation of the bulk density of the soil horizon. When reporting bulk density data, it is important to provide the water content at which the volume measurement was taken. The preferred types and quantities of specimen for bulk density are: Undisturbed small core (100 cm^3) or a large clod in 3 to 4 replications (McKenzie et al, 2008). As mentioned in the LUCAS methodology, the sampling point for the collection of soil specimens for bulk density estimation is the central sampling point of the sampling location (Stolbovoy et al 2007).

2.2.10.1 *Bulk density – core sampling (cylinder method)*

The core sampling cylinder method is generally used for the estimation of ρ_b of undisturbed soil. A rigid cylinder of known diameter (100 to 250 cm^3) and height is inserted in the soil. A sample of undisturbed soil with a cylinder's exact inside dimension is gathered and dried. Bulk density is calculated by dividing the dry mass of a soil sample by its volume and is typically measured in grams per cubic centimeter. (g/cm^3). Obtaining core samples with a core sampler is relatively simple if no stones are present.

When surface core sampling is collected, the soil surface must be cleaned from stones or vegetation. The procedure is repeated with additional cores in close proximity to get an adequate number of duplicates. The core samples must be carefully excavated, taking care not to damage the soil sample. The successfully sampled cores are packed in loose soil in plastic bags or other containers.

2.2.10.2 *Deep layer soil core sampling*

When sampling core samples in deeper soil layers, a sampling kit with a soil auger is used and is pushed or driven into the soil until reaching the desired depth and then removed. Various samplers are accessible that come with a metallic enclosure to contain the core and facilitate convenient extraction and manipulation of the sample during the processes of weighing, wetting, and drying.

2.2.10.3 *Bulk density (ρb) – clod sampling*

In a clod method after excavation of the soil pit, several clods must be selected with select with approx. volume of about 50 to 200 cm^3. The protrusions should be trimmed while roots are cut off with sensors.

2.2.10.4 Bulk density (ρb) – excavation method

The excavation method is employed to determine the soil bulk density in situations where core sampling and clod methods are not feasible, such as in the presence of a significant amount of stones or gravel, or on sloping terrains. The excavation method is appropriate for soils that have a high proportion of coarse fragments, such as those in forests. The advantage of this method is that it can be used for measuring ρ_b on virtually all types of soil except on soils with large pores. The soil volume can be determined by filling the excavated hole with a measured quantity of uniformly graded sand of a known density or water.

2.3 Analytical determination

"The organic fraction of the soil exclusive of undecayed plant and animal residues is defined as Soil Organic Matter" (SSSA, 1997) and is synonymously named as a "humus." Nevertheless, when conducting laboratory analyses, the soil organic matter (SOM) often comprises solely of the organic elements that are present alongside soil particles that pass through a 2-mm sieve (Nelson and Sommers, 1982). Soil Organic Matter is a complex mixture of animal or plant residues in different stages of decomposition, living or decaying microbiological tissue, and resistant humic substances and represents the most dynamic and active soil component of soils. From an agronomic point of view, SOM and its fractions have the most significant influence on soil fertility and plant productivity. Carbon is the predominant element found in SOM, accounting for 48 to 58% of the total weight. Therefore, organic C determinations are commonly used to quantify organic matter by multiplying the C value by a certain factor. (Nelson and Sommers 1982).

Organic carbon determination can be achieved by i) analysis of total C and inorganic C and subtraction of the inorganic from total C ii) a total C determination in the soil sample, after the destruction of the inorganic C, and III) reduction of the $C_2O_7^{2-}$ by organic C compounds in the soil sample, and subsequent quantification of the unreduced $C_2O_7^{2-}$ by oxidation-reduction titration or other colorimetric techniques.

2.3.1 TOTAL CARBON

2.3.1.1 Medium-temperature resistance furnace

In the processes involving dry combustion, the soil sample is burned in a stream of purified O_2, and the CO_2 in the effluent gas stream is absorbed by Accurate or some other absorbent and weighted. CO_2 is determined gravimetrically or titrimetric. Reference method, but time-consuming.

2.3.1.2 *High-temperature induction furnace*

Ignitions of the crucible with soil sample (0.5 g, 100 or 140 mech sieve) mixed with Fe accelerator, and Sn coated Cu accelerator, at high temperatures (>1650) in a O_2 stream. CO_2 is determined gravimetrically or titrimetric.

2.3.1.3 *Automated methods*

The sample is mixed with catalysts and is directly heated on a resistance or induction furnace in the presence of O_2 stream to convert all C to CO_2. CO_2 determination is done with gas chromatography, gravimetric or conductometric, and IR absorption spectrometry. Rapid simple, and precise. The release of contaminant CO_2 from alkaline earth carbonates is very slow when a resistance furnace is used (Rossel et. al, 2001).

2.3.1.4 *Weight loss with ignition*

The sample is heated to 430°C in a muffle furnace but gives a high level of SOM because weight loss is a result of the water, CO_2 and other volatile compounds.

2.3.2 ORGANIC CARBON

Organic carbon may be determined as a

i) Difference between the total C and inorganic C
ii) Quantities of organic C in the sample after the destruction of the inorganic C and
iii) Dichromate ($Cr_2O_7^{2-}$) oxidation with external heat ($Cr_2O_7^{2}$ oxidizes organic C in acid medium. Subsequent determination of the excessive quantities of $Cr_2O_7^{2}$ by oxidation-reduction titration with Fe^{2+} or with colorimetric methods) (Walkley and Black, 1934).
iv) Dichromate oxidation with external heat (Mebius, 1960).

Both dichromate methods are rapid, widely used, and require minimum equipment and skills. The Walkley and Black method that omits heating is not considered by the specialist as a quantitative method, while the Mebius (1960) technique that involves heat is considered as quantitative and represents the best combinations of digestion reagents, heating procedure, and titration reagents in among the dichromate methods (Nelson and Sommers, 1982). For a long period of time, a lot of efforts have been made, and solutions have been offered to improve the titration and to offer the most precise endpoint. The Simakov and Tsyplakov (1969) method with phenylanthranilic acid seems to be the most accurate and widely adopted approach.

2.3.3 BULK DENSITY

Soil bulk density has a substantial impact on soil health and is determined by various parameters such as soil porosity, mineral composition, SOC (soil organic carbon) levels, texture, structure, and moisture content. To better understand the soil's physical, chemical, and biological properties, the estimation of ρ_b is of particular importance. Close relationships of ρ_b with other soil properties are proved by many authors. Xiangsheng et al. (2016) showed that SOC has a significant influence on soil ρ_b values, while Walter et al. (2016) emphasizes the importance of accurate and efficient methods of measuring soil ρ_b when recording soil organic carbon bulk quantities.

Reproducibility and quality control of the core methods were found to be quite challenging. Many factors affect the accuracy of ρ_b measurement. Soil depth and soil types were found to affect the ρ_b measurements, which coupled with inaccuracies because of a small sample size (Walter at al, 2016). Very detailed explanations, comparison and evaluations of the methods for ρ_b measurements can be found in the work of: Campbel (1994), Casanova et al (2016), and AL-Shammary et al (2018).

2.3.3.1 *Methods for measuring bulk density*

Soil bulk density measurement methods typically fall into two distinct categories: direct and indirect methods. Direct methods differ from each other only in the way in which the sample volume is determined and it is in this respect that an assessment must be made as to the suitability of any method for a given purpose since all the methods have some limitations (Campbel, 1994). Although direct methods are well-established and use affordable equipment, they are time consuming and not suitable for rapid and accurate bulk density estimation. To overcome these limitations, indirect methods have been developed. These methods are based on the principle of scattering and attenuation of nuclear radiation when interacting with the soil sample and provide an indirect measurement of bulk density. Indirect methods involve calibrating the apparatus by means of samples of known bulk density. (Campbel, 1994).

2.3.3.2 *Core sampling*

The core sample method is widely employed for estimating the bulk density of agricultural soils. (Casanova et al., 2016, FAO 2023). In this method, an open-ended, metal cylinder is either pressed or hammered into the soil. The core sampling method is suitable for cohesive soils with water contents close to field capacity, which is important for heavy clayey soils with a high coefficient of swelling and shrinking, which can pose significant errors in the results. The approach is also vulnerable to errors that may occur due to compression or fragmentation of the core during the insertion of the cylinder.

In the lab, the mass of the cylinder with the soil sample (before drying) is recorded. One cap of the cylinder is removed, and soil samples are dried at 105 °C ±5 °C for 24 hours or until the constant weight is achieved, to obtain the dry mass of the soil. After drying the cap is fitted back to the cylinder and the samples are placed in a desiccator until room temperature is reached. The weight of the cylinder and the oven-dried mass is recorded.

The bulk density is calculated as a ratio of the net weight (minus the mass of the cylinder) of the dry soil mass (g) with the volume of the cylinder (cm^3) multiplied by 100, to the nearest 0.01 g/cm3 (FAO_SOP).

2.3.3.1 Clod method (paraffin-sealed clod)

The clod method, which is conducted in a laboratory environment, is the second most used methodology for assessing soil ρ_b (Casanova et al., 2016). In this method, soil ρ_b is measured by calculating soil mass and volume using paraffin wax, saran rubber, or wax mixtures. The method is time-consuming due to its complex and slow experimental process. The clods must be stable and have a size limit of 4–10 cm in diameter. The immersion and weighing of a coated clod is a complex and demanding procedure, with the potential for increased errors in measurement. Casanova et al. (2016) found that the clod approach overestimates values compared to other direct procedures since it does not consider inter-aggregate pores or gaps.

2.3.3.2 Excavation method (volume replacement)

On the field, a hole approximately 10 cm in diameter is excavated and all material from the hole is saved in a container. The soil sample collected is dried in a laboratory at 105° C for approximately 24 h, depending on moisture content and its mass and water content determined.

The sample volume is determined by filling the excavation with sand from a sand container (sand bottle). The difference in weight of the sand container before and after filling the excavation is recorded. The bulk density of the sand in the bottle is determined with a calibration test in which sand from the bottle is used to fill cylindrical containers of known dimensions (Campbel 1944). Thus, the volume of the excavated hole can be calculated and hence the bulk density of the soil.

There are several potential sources of error in the method, but most of them can be avoided. It is crucial that the sand used is dry, and free of soil debris if sand is reused. Regular calibration tests are the best possible way to avoid such errors. The best practice is, if sufficient sand quantities are available, to avoid reuse. Typically, 0.2-2.0 mm sand is used in the excavation method. However, the uniformity of the graded material is more important on the variation in sand bulk density than its actual size. Many authors propose different variations of this method to improve its accuracy, like Crnica (cit. Campbel 1994) who used a sand bottle with a calibrated volume so the difference in sand volume before and after filling the excavation corresponds to the volume of the hole, so a knowledge of the sand bulk density is not required.

2.3.3.3 *Indirect methods*

To overcome these limitations, a second group of methods has evolved, in which the attenuation or scattering of nuclear radiation by the soil sample is used to give an indirect measurement of bulk density. This is achieved by calibrating the apparatus by means of samples of known bulk density.

2.3.3.4 *Gama radiation*

The gamma radiation method is commonly used to measure soil ρ_b and involves the use of gamma backscatter density gauges and transmission gauges. The gamma-ray transmission method is a precise technique for studying soil physical parameters. The radiation approach allows for precise identification of soil ρ_b due to the minimal impact of gamma radiation transmission on the soil's physical structure. Although the backscatter gauge is widely used, this methodology is costly and complex requiring high-tech equipment and skilled operators. Soil type and instrument calibration significantly influence measurement accuracy (Campbell 1994).

2.3.3.5 *Regression methods (PTFs)*

Regression techniques, also known as Pedotransfer Functions (PTFs), are fundamental in modeling cand be used indirectly to estimate the soil ρ_b. Different approaches, such as multiple linear regression, decision tree analysis, and grouping methods of data management, have been used to enhance the PTFs for determining soil ρ_b. Numerous studies have been tested different regression models to evaluate the ρ_b using other soil properties such as soil organic carbon content, texture, structure, depth, and water content, and field and climatic conditions (Al Shammary et al, 2018+++).

2.4 Spectral methods

2.4.1 INTRODUCTION

According to Viscarra Rossel et al. (2006) standard soil chemical and physical laboratory analysis has been employed to enhance our comprehension of soil and evaluate its quality and functions. There is a worldwide need for gathering larger quantities of high-quality, affordable soil data to be utilized in environmental monitoring, modeling, and precision agriculture by developing more effective methods that save time and money. Diffuse reflectance spectroscopy is a viable option to improve or substitute traditional soil analysis methods, since it effectively addresses some of their drawbacks. Spectroscopy is a rapid, cost-effective, non-destructive, relatively simple, and occasionally more precise method compared to traditional analysis. In addition, a single spectrum enables the simultaneous measurement of many soil characteristics, and the approaches may be easily adapted for field use.

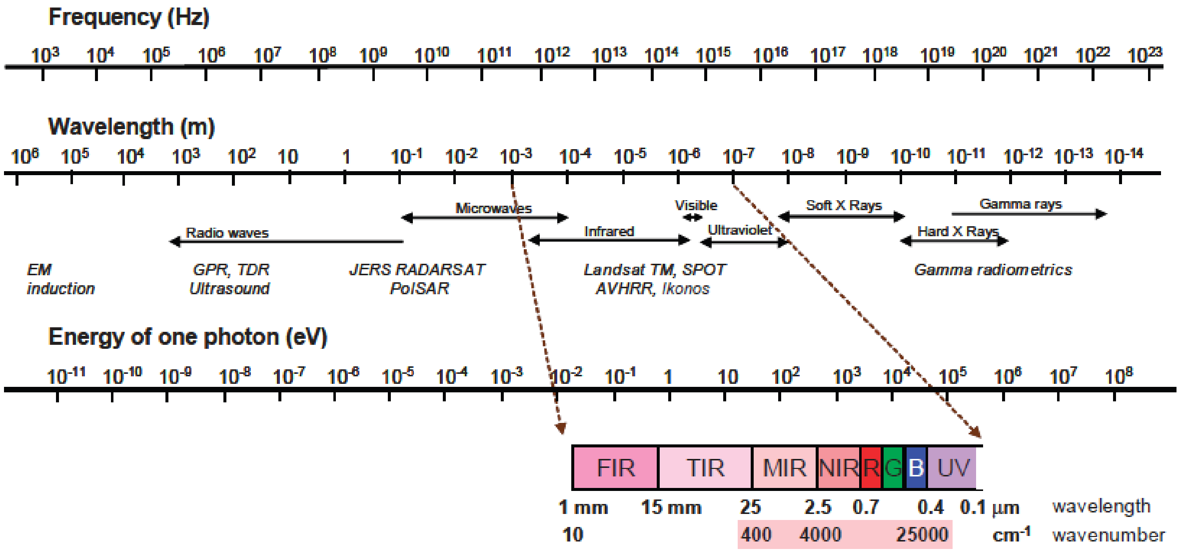

Figure 2.1. The electromagnetic (EM) spectrum showing the visible and infrared bands (after McBratney et al., 2003).

According to Smith et al (2020) the reflectance of light on soil in the infrared region (Figure 1) provides the methods for measuring SOC concentration, specifically, in visible (VIS) 400–700 nm, near infrared (NIR) 700–2500 nm and mid infrared (MIR) 2500–25,000 nm. Predicting the soil carbon percentage of unknown samples may be achieved by utilizing spectral data and a statistical model that relies on a spectral library.

2.4.2 NEAR- AND MID- INFRARED SPECTROSCOPY

For measuring the C content of soil, spectroscopic methods including Near-Infrared (NIR) and Mid-Infrared (MIR) spectroscopy are highly appealing among the inexpensive and simple alternative techniques. The last forty years have seen a significant development of these techniques in agriculture, with a boom beginning in the late 1980s. These techniques measure the composition of grains, fruit and vegetables, meat, etc. (Bellon-Maurel & McBratney, 2011).

According to Bellon-Maurel & McBratney (2011), the main difference between the two methods lies in the fact that absorption in mid-infrared spectroscopy is related to the fundamental bands of molecular vibration, while absorptions in the near-infrared are related to the overtones and combinations of these fundamental bands. As a result, in comparison to the MIR range, the NIR range has lower band specificity. Another thing to consider is that light diffuses far more in the near-infrared than it does in the mid-infrared. Consequently, elements that influence light diffusion, such as aggregate size and porosity in the physical structure, as well as the presence of water, which alters the refractive index and, consequently, light diffusion, will have a significantly greater impact on NIR spectra (Williams and Norris, 1987)

Absorbance at the electromagnetic radiation wavelengths in the MIR region (2,500–25,000 nm) is a consequence of fundamental molecular vibrations. Meanwhile, it is more challenging to characterize combination bands and overtones than those in the MIR area are the cause of the absorbance in the visible-near-infrared (vis-NIR; 350–2500 nm) region. Regarding field applications and instrument portability, Vis-NIR outperforms MIR (Ng, 2022). However, thanks to technological advancements, portable MIR instruments are now also available (Ji et al., 2016; Hutengs et al., 2019). According to Soriano-Disla et al. (2014), MIR is also more sensitive than vis-NIR to the organic and mineral components of soils. Numerous studies have demonstrated that MIR, compared to vis-NIR, can produce more reliable predictions of several soil parameters (Reeves, 2009; Ng et al., 2019).

For measuring C, MIR spectroscopy performs slightly better than NIR, with prediction errors typically 10–40% lower than with NIR. Both NIR and MIR exhibit significant prediction errors when the validation and calibration samples differ significantly, which are mostly explained by bias resulting from poor fit to the new data (Bellon-Maurel & McBratney, 2011). Multiple research studies have shown that the most effective near-infrared (NIR) range is within the 1650 to 2500 nm spectrum (Hummel et al., 2001; Mouazen et al., 2007; Lee et al., 2009; Morgan et al., 2009).

2.4.3 VISNIR SPECTROSCOPY

Our knowledge of soil functions and the ways in which land use and climate change influence soil organic carbon (C) reserves can be improved by measuring the bulk density of soil. The existing bulk density measurement techniques are costly, time-consuming, prone to mistakes, and confounded by the requirement to measure below the soil's surface. When describing the temporal and spatial (lateral and vertical) change of soil bulk density and associated parameters, these flaws become more apparent. A method that measures the bulk density of 1-meter soil cores that are sampled fresh, wet, and in the field using a combination of visible-near-infrared (vis-NIR) spectroscopy and gamma-ray attenuation was developed by Lobsey & Viscarra Rossel (2016).

The availability of accurate soil measurements continues to be an obstacle to applications like precision agriculture and digital soil mapping, despite the ongoing demand for soil data in these areas. The high cost of collecting soil samples and conducting laboratory analyses usually limits the amount of information available on soil attributes. By substituting for or enhancing conventional analytical techniques, systems like visible near-infrared spectroscopy (VisNIR) can lower the expenses associated with laboratory analysis (Ackerson et al., 2017).

Numerous soil parameters have been measured using visible-near-infrared spectroscopy, or VisNIR. In the lab, VisNIR is often applied to ground and air-dried soils. It is now possible to obtain VisNIR spectra from in situ soils thanks to recent advancements in VisNIR apparatus. This method offers several benefits, including the ability to test soil parameters without requiring the collection, preparation and laboratory analysis of samples. (Ackerson and others, 2017).

2.4.4 STATISTICAL MODELS

Several statistical approaches have been developed to estimate several physical and chemical properties from spectral data. Four of them are described below (Haghi et al., 2021).

2.4.4.1 *Partial least square (PLS)*

A popular linear regression technique that predicts the relationship between the spectra and observed values using latent variables is the partial least square (PLS) approach. The latent variables capture the highest correlation between the spectra and the observed values, while also reducing the dimension of the original spectra. The purpose of the PLS technique is to develop a model with the ideal number of latent variables by extracting the latent variables from the spectral data (Haghi et al. 2021). The literature (Abdi, 2003, 2010) contains the PLS method's specifics.

2.4.4.2 *Support vector regression (SVR)*

Over the past few years, support vector machines—a data mining technique—have gained a lot of popularity. Initially, this technique was created to solve classification issues using the concept that Vapnik (1995) first presented. Subsequently, this technique has been expanded to address regression problems as well. This method's fundamental idea is to map the non-linearly separable input data onto a higher dimensional feature space, where a hyperplane can be used to separate the data points linearly. The data is projected into a higher dimensional space using kernel functions (linear, non-linear, sigmoid, or radial basis). Each kernel function requires a distinct set of parameters to be adjusted (Haghi et al., 2021).

2.4.4.3 *Convolutional neural network (CNN)*

CNN is a subset of artificial neural networks and a deep learning technique. Several hidden layers, including convolutional, down sampling, flatten, fully connected, and optional layers (such as batch normalisation), are added to the input and output layers of a CNN model (Haghi et al., 2021).

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3 MONITORING OF SOIL QUALITY

3.1 Introduction

The performance of soil to accomplish their functions depends on its soil quality (SQ), making its measurement by Soil Quality Indices (SQI) a crucial aspect. But, because of the multi-functionality of the soil, measuring SQ is by no means easy. Direct quantification of soil functions requires costly methods and labor (Wiesmeier et al., 2019) or in some cases, it is not possible to do so directly and must be inferred from certain soil characteristics (Cardoso et al., 2013). Therefore, the SQI to be adopted will depend on the indicators used to assess these functions, and there is not a universal list of SQ indicators widely accepted, since different authors define SQ in different ways.

The soil quality concept was introduced in the 1960s and 1970s by authors like Klingenbiel and Montgomery (1961 in Costantini & Priori, 2023) Mausel (1971 in Bünemann et al., 2018) or Warkentin and Fletcher (1977 in Wienhold et al., 2008) as a framework to guide use and allocation of labor, fiscal, and other inputs to meet increasing demands being placed on agriculture. Since then, there has been some terminological controversy (Bonfante et al., 2020; Karlen et al., 2008) about the appropriateness of the use of the terms Soil Quality, defined as the capacity of a soil to function within ecosystem boundaries to sustain biological productivity, maintain environmental quality, and promote plant and animal health (J. W. Doran & Parkin, 1994; Soil Science Society of America, 2024), Soil Health, defined as the capacity of soil to function as a vital living system, within ecosystem and land-use boundaries, to sustain plant and animal productivity, maintain or enhance water and air quality, and promote plant and animal health (J. W. Doran & Zeiss, 2000) or even Soil Capability, defined by Bouma et al. (2017) as the intrinsic capacity of a soil to contribute to ecosystem services, including biomass production, although this concept has had less impact in the current scientific literature.

In any case, when speaking of Soil Quality or Soil Health, it is necessary to emphasize the dynamic dimension of the concept, as it describes the situation or condition of a soil as a consequence of its current or past management, as opposed to inherited soil quality, which is a reflection of soil-forming factors and includes soil attributes that will not generally respond to recent management changes (Karlen et al., 2008). Based on this dynamic aspect, authors such as Bünemann et al. (2018) and Moebius-Clune (2017) conclude that the terms Soil Quality and Soil Health can be considered to some extent as equivalent since the original concept of Soil Quality has evolved to present soil as a living, finite, non-renewable and dynamic resource (Muñoz-Rojas, 2018).

Multiple attempts have been made to develop indices to synthetically assess Soil Quality (de Paul Obade & Lal, 2016a, 2016b; Jian et al., 2020; Karlen & Stott, 2015; Mukherjee & Lal, 2014; Trasar-Cepeda et al., 1998), although the acceptance of a universal soil quality index (Dumanski et al., 1998) is a highly debated concept, which may be understood as a somewhat "institutionalized" quality concept (Sojka & Upchurch, 1999). However, most of them have in common that they are based on the establishment of a set of biotic or abiotic indicators as the basis of the assessment, reflecting the multidimensionality of the soil system, and differing subsequently in the way they interconnect these indicators and reduce their collinearity to obtain the quality index (Bünemann et al., 2016; Kosmas et al., 2014).

3.2 Procedure to build soil quality indices

3.2.1 SOIL QUALITY INDICATORS.

The assessment of soil quality is related to the evaluation of the ecosystem services provided by soil. It has been stated that evaluating soil quality requires taking into account one or more soil functions or ecosystem services (Bouma, 2014; Reinhart et al., 2015), although authors such as Vogel et al. (Vogel et al., 2018) establish differences between the two concepts arguing that "Soil functions are produced by complex interactions of natural processes and are the basis for the functioning of terrestrial ecosystems, while ecosystem services and resource efficiency are defined in the context of the current human perception and may change according to the societal context".

Once an agreement is reached about the functions of the soils we want to measure in a certain ecosystem, the next task is to select the most appropriate soil quality indicators to calculate the SQI. Soil quality indicators have been defined as "measuring instruments that provide information on properties, characteristics and processes, and serve to assess the effects of management practices on a soil at a given point in time" (Astier-Calderón et al., 2002). Also, they are defined as measurable biotic or abiotic soil properties in a time- and cost-efficient way that contain sufficient information for the quantification of soil functions and that can be reproducible with a relatively low level of expertise. (Vogel et al., 2018; Wiesmeier et al., 2019).

The concept of 'within ecosystem boundaries' for soil functionality in both Soil Quality and Soil Health definitions implies that SQ must be referred to the ecosystem where it is measured and that each soil has a different capacity to fulfil the different soil functions (Bloem et al., 2006). For this reason, Sánchez-Navarro et al. (2015) state that the SQ indicators (and the resulting SQI) must consider the specific ecosystem in which we work and the soil functions we intend to preserve, especially those of relevance in the experimental site. According to this, Drobnik et al. (2018), indicate that frameworks for the proposal of soil quality indicators are always discipline-referenced and context-focused. Therefore, meaningful soil quality comparisons can only be made for a series of soils, at a specific location, with a known management history. Quality comparisons between different soils are practically meaningless due to differences in the factors inherent in soil formation (Karlen et al., 2008). Nevertheless, authors like Kuzyakov et al. (2020) propose an approach that might allow comparison of soil quality indices in different areas.

There is not a universal list of soil properties that serve as suitable soil quality indicators for all regions, so a judicious selection of the most applicable indicators must be done (Burns et al., 2006). According to Doran and Parkin (J. W. Doran & Parkin, 2015), the criteria to select the indicators of soil quality primarily pertain to: (i) their usefulness in specifying ecosystem processes; (ii) their capacity to include physical, chemical, and biological characteristics; (iii) their responsiveness to changes in management and climate.; and (iv) whenever possible, being components of existing databases. In relation to sensitivity to management, Vogel et al. (2018) propose an interesting classification of soil attributes or properties according to their characteristic time scale of change: "inherent soil properties" that depend on parent material and soil formation stage, and are not immediately affected by soil management "soil state variables" observable soil attributes that can change on short time scales of minutes to days in response to external forcing and, "functional soil characteristics" falling between the other two categories, which might change abruptly in response to external forcing but has an intermediate time scale of change (days to months) as a result of internal processes and interactions.

Benedetti and Dilly (2006) add to the above criteria the need for indicators to be understandable and useful for land managers, as well as easy and inexpensive to measure. Stone et al. (2016) also highlight some other aspects concerning the necessary skills of the person monitoring the soil, availability of the necessary equipment in laboratories, the time required for sampling and measurements, the amount of sample needed for laboratory analyses, or the reproducibility of the results. Rinot et al. (2019) further emphasize the need for indicators to reflect the connection between soil functions and management objectives.

Several authors and institutions have developed a list of indicators over the last decades, accepted by the scientific community, which consider physical, chemical and biological properties of soils and meet the described requirements to be a good soil quality indicator. (Cárceles Rodríguez et al., 2022; J. W. Doran & Parkin, 1994; Moebius-Clune, 2017; NRCS, 2008; Oliver et al., 2013; Seybold et al., 1997) Other authors introduce biochemical indicators, as a category, because of the difficulty of separating chemical and biological processes due to their dynamic and interactive nature and their sensitivity to any short-term management changes (Bonanomi et al., 2011; Brennan & Acosta-Martínez, 2019; Mondini et al., 2019; Saikia et al., 2019; Schoenholtz et al., 2000; Scotti et al., 2015).

However, a survey of 170 soil databases at European level showed that although over 70% of the country soil databases cover most of the primary pedological and chemical parameters, water content, contamination with organic pollutants, and biological parameters are the least often reported parameters. (Cornu et al., 2023). According to these authors, such differences will have consequences when developing an EU policy on soil quality and using the data to derive soil quality indicators. Similar results have been found by Valani et al. (2021) who found that physical indicators appear in 80% of the 92 reviewed papers on soil quality assessment in integrated crop-livestock-forest systems, chemical indicators in 70% of the studies and biological indicators in only 33%. In addition, they indicate that only 20% of the studies integrate the indicators in an SQI. Moreover, several disparities were identified in the methods employed for soil collection, preparation, and analysis, necessitating the implementation of harmonization processes to obtain a useful interpretation and to establish reference values for each indicator (Hughes et al., 2023).

Bünemann et al. (2018) found in a review of 62 publications and Bastida et al. (2008), also found in a review of 15 publications, that total organic matter/carbon and pH are the most frequently proposed soil quality indicators. After these, both groups of researchers found available phosphorus, various indicators of water storage, bulk density, texture, available potassium and total nitrogen to be the most frequently used. Other indicators frequently found by these and other researchers (Allek et al., 2023; Brichi et al., 2023; T. Yang et al., 2020) were: (i) Chemical indicators: electrical conductivity, cation exchange capacity, available nitrogen, heavy metals, other macronutrients, sodicity, salinity, micronutrients and labile C and N; (ii) physical indicators: structural stability, soil depth, penetration resistance, hydraulic conductivity, porosity, aggregation and infiltration; and (iii) biological indicators: soil respiration, microbial biomass, N mineralization, soil enzymes and earthworms. Zornoza et al. (2015) agree with this presentation of soil quality indicators but warns of the virtual absence of human health indicators or exposure pathways in soil quality assessments. Basak et al. (2022) also highlights the need to pay special attention to the selection of analytical techniques for the measurement of physical, chemical, and biological indicators of some special soils, such as salt-affected or alkaline soils.

Costantini and Priori (2023) propose a grouping of soil quality indicators, susceptible to be affected by changes in soil management, according to their relevance in providing specific functions, concerning (i) water supply; (ii) oxygen supply; (iii) nutrient supply; (iv) regulation of runoff; (v) sediment production; (vi) groundwater recharge; (vii) purifying capacity and regulation of contaminants; (viii) carbon sequestration; (ix) biological activity and cycling of organic matter and nutrients; and (x) biodiversity pool, and propose a table with the most relevant and commonly used in monitoring programmes, which, to a large extent, coincides with those previously stated by Bünemann et al. (2018) and Bastida et al. (2008)

Other authors use scientifically well-established composite indices as basal indicators of soil quality that can participate in the development of the soil quality index. Thus, Jiang et al. (2025) suggest a standardized framework for evaluating soil quality that considers heavy metal contamination and microbial-induced resilience, by using well-known indices like Shannon-S, Shannon-F, Pielou-S, Chao1-F, Geo-accumulation index or Nemerow's pollution index and build two new indexes Soil Resilience Index, the Soil Contamination Index, to calculate the SQI.

The advent of new technologies, such as near-infrared spectroscopy (NIR), portable X-ray fluorescence, and remote sensing, along with other non-destructive methods like X-ray tomography, offers the ability to quickly and inexpensively access a wide range of soil properties (Askari et al., 2015a; Chabrillat et al., 2019; Chaudhry et al., 2024; Muñoz-Rojas, 2018; Paz-Kagan et al., 2014; Silva et al., 2023). Real-time continuous soil monitoring (RTCSM) seems promising (Fan et al., 2022). Machine learning and artificial intelligence are being used to develop models to estimate soil quality from the processing of multidimensional data obtained with remote sensing (Diaz-Gonzalez et al., 2022). Significant progress has been made in biological and biochemical indicators of soil quality over the past decade. In addition to the widespread adoption of biochemical, physiological, and metabolic techniques for determining microbial biomass and respiration (Ashraf et al., 2022; G. Li & Wu, 2018), the characterization of soil microbial communities is increasingly used as an indicator of soil biological quality (Orgiazzi et al., 2015). The use of multiomics approaches can provide a more accurate and realistic view of microbiome, which can be used for the assessment of soil quality (Maurya et al., 2020). These techniques are also beginning to provide a deeper understanding of the functionality of different taxa in soil and the relationship between microbial diversity and ecosystem functionality.

To include biological indicators in soil quality assessments, Creamer et al. (2022) have developed an integrated framework for defining the role of soil biota in soil multifunctionality, using the hierarchical multi-criteria decision structure following Debeljak et al. (2019). Bhaduri et al. (2022) classify the bio-indicators that have emerged as a consequence of these new techniques into four categories: (i) Physiological, which includes indicators such as Microbial Biomass Carbon, N or P, and Sustrate Induced Respiration; (ii) Metabolic, which includes the analysis of sterols, proteins or common enzymes for microbial activity, such as dehydrogenase, phosphatase, urease or beta-glucosidase; (iii) Functional, BiologTM or PLFA for analysis of microbial communities; and (iv) Molecular, based on the extraction of DNA or RNA from soil.

Soil Quality assessment needs to include baseline or reference values to enable identification of management effects on soils (Bünemann et al., 2018; Karlen et al., 2008). This baseline can be established at the first time a Soil Quality Assessment is carried out, so that subsequent assessments can determine the trend of both the SQI and the indicators used in response to the management decisions made.

Alternatively, this baseline can be established based on an undisturbed ecosystem with the same soil, climatic conditions and vegetation cover as the area to be assessed. (Allek et al., 2023; Bai et al., 2018). For this to be possible, it will also be necessary to use standard methods for both soil sampling and analysis of selected indicators. (Nortcliff, 2002).

However, the need for continuous assessment of soil quality over time by soil sampling and analytical procedures may involve high costs, which may discourage the land manager or may overextend the time interval between two successive assessments (Maharjan et al., 2024). In this sense, authors such as Read et al. (2016) propose the Landscape Function Analysis (LFA) method as a conceptual, methodological and interpretative framework that allows a quantitative assessment of soil functions. The method is based on the use of 11 visually acquired soil surface assessment indicators, which relate specific soil properties and processes. These indicators are used to obtain three integrated indices: soil stability, infiltration and nutrient cycling, strongly linked to the provision and regulation of ecosystem services, including the retention of soil, the cycling of water and nutrients, the production of biomass, and the storage of carbon.

3.2.2 STANDARDIZATION OF SAMPLING AND ANALYSIS METHODS FOR SOIL QUALITY INDICATORS

To achieve a standardization of sampling and analysis methods, The International Organization for Standardization, ISO, works in the development of international technical standards, contributing to all the Sustainable Development Goals (SDG) (Figure 1).

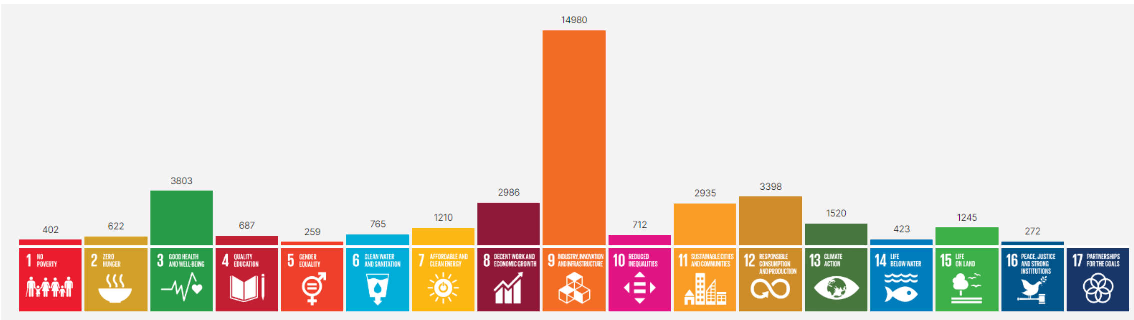

Figure 3.1. ISO standards applicable to each SDG. Source: ISO, n.d.

The international standards on environmental sustainability provide a transparent and pragmatic approach to attain operational excellence, adhere to legal obligations, and fulfill the expectations of stakeholders. Implementing these ISO standards enables firms to establish themselves as frontrunners, achieve cost and resource savings, and earn confidence and respect. (ISO, n.d.). Soil quality standards are part of this category, which guide sustainable land use and soil management practices to protect and improve soil health, essential for agriculture, biodiversity, and carbon sequestration.

An ISO standard is reviewed every 5 years. There are currently 234 soil quality standards, with 215 published and 19 'under development'; in other words, a draft is being reviewed by the committee to later replace other standards (ISO, n.d.).

In general, ISO 9001:2015 standard is a globally recognized standard for quality management that contributes to SDG 1, 9, 12, and 14. This standard helps organizations and industries by defining how to establish, implement, maintain and improve a quality management system. ISO 9001:2015/Amd 1:2024 provide additional content to this standard, which will soon be replaced by ISO/CD 9001.

Among the various very important standards of soil quality, most of them refer to methodologies for the evaluation of several soil quality indicators and properties, both at field and laboratory levels; even possible recording and monitoring of changes in dynamic soil properties, by ISO 23992:2022. Many of them are related to sampling, highlighting:

- ISO 18400-301:2023 Part 301: Sampling and on site semi-quantitative determinations of volatile organic compounds in field investigations.
- ISO 18400-206:2018 Part 206: Collection, handling and storage of soil under aerobic conditions for the assessment of microbiological processes, biomass and diversity in the laboratory. This standard contributes to the SDG 3, 13 and 15.
- ISO 18400-203:2018 Part 203: Investigation of potentially contaminated sites. This standard contributes to the SDG 3, 12, 13 and 15.
- ISO 18400-104:2018 Part 104: Strategies; ISO 18400-205:2018 Part 205: Guidance on the procedure for investigation of natural, near natural and cultivated sites, and ISO 18400-202:2018 Part 202: Preliminary investigations. These standards contribute to the SDG 2, 3, 12, 13 and 15, and, together, are a new version and revise ISO 10381-4:2003.
- ISO 18400-107:2017 Part 107: Recording and reporting. This standard contributes to the SDG 15.
  - ISO 18400-102:2017 Part 102: Selection and application of sampling techniques, previously ISO 10381-2:2002 and ISO 10381-6:2009. This standard contributes to the SDG 15.
  - ISO 18400-100:2017 Part 100: Guidance on the selection of sampling standards. This standard contributes to the SDG 15.

In relation to soil carbon content, ISO 23400:2021 provides the principles for the determination of the stocks of organic carbon and nitrogen in mineral soils at the field scale, as well as their variations, ISO 20951:2019 offers suggestions for the measurement of the fluxes of greenhouse gases (CO_2, N_2O, CH_4) and ammonia (NH_3) between soils and the atmosphere, ISO 17184:2014 determines carbon and nitrogen by near-infrared spectrometry (NIRS), ISO 16703:2004 and ISO 10693:1995 determines carbonate and hydrocarbon in the range C10 to C40 by gas chromatography, respectively. Besides, ISO 16072:2002 establishes laboratory methods for determination of microbial soil respiration. Other standards such as ISO/AWI 21251 and ISO/CD 17505 will soon be published, which offer guidelines for determining the amount of organic carbon stored in soils based on their biogeochemical stability or residence time, as well as the temperature-dependent differentiation of total carbon (TOC400, ROC, TIC900) in soil and waste. On the other hand, there are also specific standards that guarantee the proper use of agricultural machinery and thus soil and environmental health, such as ISO 8947:1993, even others related to agricultural soil water management (e.g. ISO 16075-6:2023).

Finally, it is important to note that there are also national organizations and standards equivalent to ISO. For example, UNE is the Spanish Standardization organization in ISO and others such as IEC, CEN, CENELEC, ETSI and COPANT. It establishes 135 current soil quality standards with international equivalences (UNE, n.d.).

3.2.3 FROM SOIL QUALITY INDICATORS TO SOIL QUALITY INDEX

Soil quality indices (SQI) have been defined as the 'minimum set of parameters that, when interrelated, provide numerical data on the capacity of a soil to carry out one or more functions (Bastida et al., 2008). The different SQI are obtained by integrating into a formula different soil indicators that represent the set of soil properties relevant for SQ status. The development of effective, simple and reliable SQI must also allow for measuring the changes of SQ over time, in response to changes in land use, and to quantify the effects of agricultural management practices on SQ.

Many of the soil quality indicators are closely related and provide redundant information. For simplicity and a better understanding and calculation, the number of indicators can be reduced by taking into consideration the correlation between them, making it important to select those indicators that are more appropriate for fulfilling the chosen soil function quantified by the SQI. This SQI should be selected with the minimum set of indicators (minimum data set or MDS) that, when integrated in a formula, provides numerical data on the capacity of a soil to carry out one or more functions (Acton & Padbury, 1994; Andrea et al., 2018; Raiesi, 2017; Thakur et al., 2022).

Different methods can be used to reduce their number in order to build a meaningful and easily understandable SQI: algorithmic, arithmetic or statistical methods such as Analysis of Variance (ANOVA) (D'Hose et al., 2014; Rinot et al., 2019), Principal Component Analysis (PCA) (de Andrade Barbosa et al., 2019; Mukherjee & Lal, 2014), Partial Least Squares-regression (PLS-R) and Partial Least Squares-discriminate analysis (PLS-DA) (Paz-Kagan et al., 2014), Redundancy Analysis (RDA)(Costantini & Priori, 2023), Factor Analysis (Vasu et al., 2016) and expert opinion (EO) (Dal Ferro et al., 2018; Giannetti et al., 2009).

Initially, MDS selections were based on expert opinions (J. W. Doran & Parkin, 1994). Subsequently, the reduction in the number of indicators was performed by multivariate techniques, with multiple regression and principal component analyses being the most widely used. Principal component analysis is a well-known procedure to lessen unnecessary data by correlating variables. With the above-mentioned methods, the number of soil quality indicators is often reduced between 6 and 8. Andrews, Karlen, et al. (2002) concluded that both, the expert opinion and statistical methods are valid to select the minimum set of indicators while reducing their number. The main disadvantage of the statistical methods resides on the need for a wide set of data.

After the selection, MDS indicators are applied a scoring function based on their actual effects on the accomplishment of the selected soil functions, where every indicator measurement is first interpreted and then converted to a value usually between 0 and 1 using standardized scoring functions (Andrews, Karlen, et al., 2002; I. Hussain et al., 1999). This scoring can be done by either linear or non-linear procedures (X. Li et al., 2019). Andrews, Karlen, et al. (2002) compared linear and non-linear methods for scoring, and concluded that they do not differ much, but that the latter requires a deeper knowledge about each indicator. Nonetheless, they recommended non-linear methods, because they are often more representative of the complexity of the soil functions compared to the linear method for scoring. Thus, generally, non-linear scoring methods are preferred over linear scoring to represent this complexity. Assessments of soil quality indicators using standard non-linear scoring functions include i) more is better, ii) less is better, iii) optimum range, or iv) undesirable range (Karlen & Stott, 2015), with more is better and less is better being the most used in soil science, although a combination of them is frequently used depending on the soil quality indicator.

Andrews, Karlen, et al. (2002) explain the shape of the curves used for scoring as follows: Some indicators follow typically a variation of a bell-shaped curve where the 'mid-point is the optimum'; a sigmoid curve with an upper asymptote for the scoring 'more is better', or a sigmoid curve having a lower asymptote for the 'less is better' function. The assignment of the curve can be determined according to agronomic and environmental function using literature review and by expert opinion. Unfortunately, as many authors underline, the shape of the curves and, therefore, the scoring of soil quality indicators, will always remain controversial partly due to the lack of information, partly due to the conflictive curvilinear pattern of various indicators and partly because the use of expert opinion is controversial itself (Merrington et al., 2006).

After the scoring of soil quality indicators by the chosen methods, additive and weighted additive SQI are built. In the simple additive index, the values (or ranges) of the soil quality indicators are scored and the SQI is the summation of each individual value (Amacher et al., 2007; Mukherjee & Lal, 2014). Nonetheless, if the evaluated soil functions differ significantly in importance, then a weighting of the soil indicators representing the desired soil functions is required. In fact, the first multiparametric SQI established by Karlen et al. (1994a) already weighted the selected soil indicators based on their role concerning the predefined goals defining SQ. This approach has been used to assess the impact of management practices for agricultural soils (I. Hussain et al., 1999; Lima et al., 2013) and for natural forests (Melo Filho et al., 2007). Although the systems based in Karlen and Stott (2015) have been widely adopted, weighting of the indicators is subjective and is not supported by any statistical method.

Finally, the obtained SQI values from the equation in different soil conditions and/or over time are discussed and eventually validated against the perceived functioning of the natural ecosystem, while in agricultural soils, they are more often validated against yield data, and sometimes against Sustainable Yield Index (Askari et al., 2015a; I. Hussain et al., 1999; S. Li et al., 2016; Mukherjee & Lal, 2014; Sharma et al., 2005). Figure 2 summarizes the procedure followed to select the best SQI.

Kuzyakov et al. (2020) propose an approach that would allow comparison of soil quality indices in different areas. The SQI-area approach is based on a comparison of the area within the radar plot produced from the group of individual soil parameters that have been selected to compose the SQI. Each individual soil parameter must be standardized to unity (1.0), using the base value of the indicator corresponding to an undegraded soil (in most cases a natural ancestor or analogue soil). This standardization guarantees, according to the authors, the comparison of any SQI with any number of parameters. From the standardized values, a radar diagram will be constructed for each soil so that the comparison of the areas covered by each soil will reflect the differences in quality.

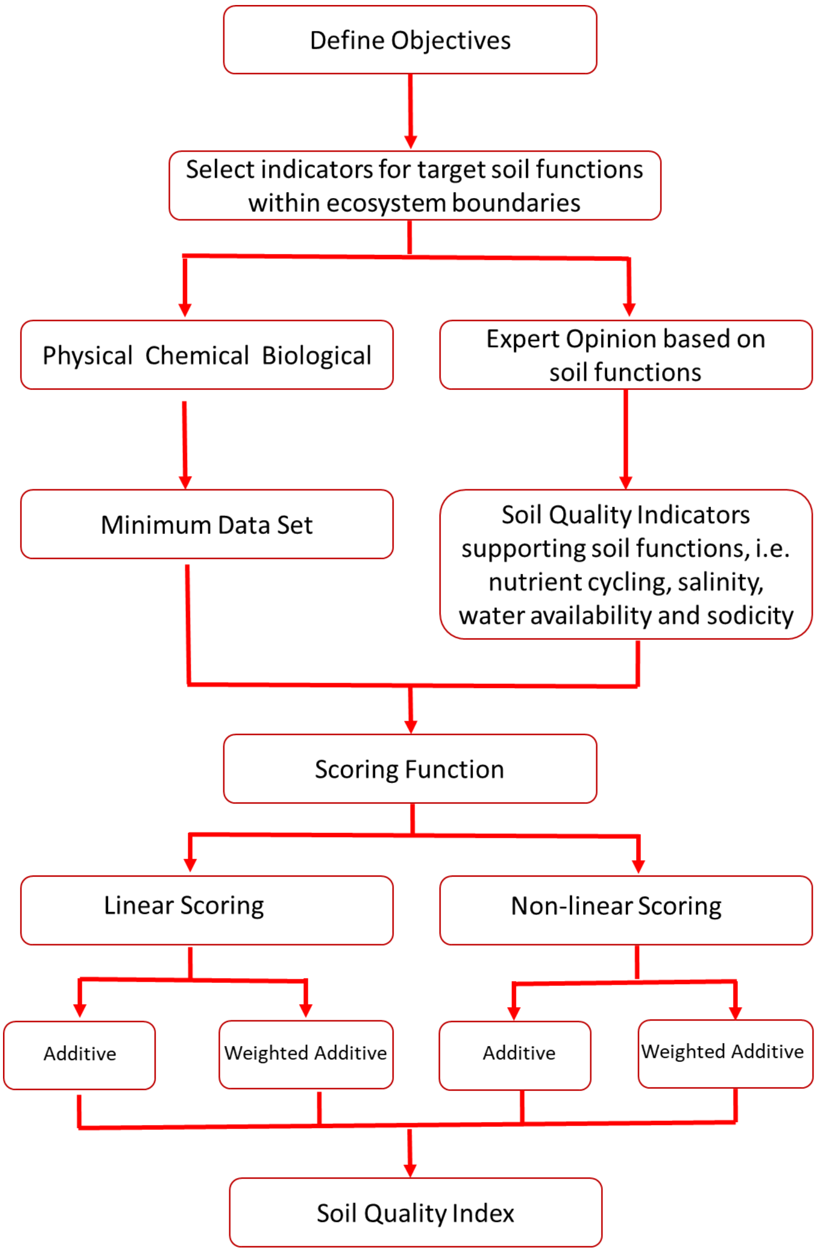

Figure 3.2. Procedure to establish a Soil Quality Index. Based on Thakur et al. (2022) slightly modified

Efforts to apply satellite or airborne imaging spectroscopy to estimate SQI and crop productivity are emerging fields. Several studies have attempted to apply near-infrared (NIR), mid-infrared (MIR), and vis-NIR spectroscopy to assess SQ in both field and laboratory settings because these methods are rapid, cost-effective, and nondestructive (Liu et al., 2020; Xia et al., 2018; Zornoza, Guerrero, et al., 2008).

3.3 Common soil quantity indices

An integrative soil quality index of worldwide use is often desired but, besides the difficulty inherent to its construction, its utility is dubious, since soil quality is often better evaluated for the accomplishment of specific soil functions that vary according to the type of soil (Simon et al., 2022). Therefore, there is no extensive SQI that can be accepted as a universal approach across scales and regions.

Bastida et al. (2008) reviewed many different SQIs and developed an understanding of their advantages and disadvantages. The authors first distinguished between simple and multi-parametric SQI. They mentioned simple SQI such as the metabolic quotient (qCO2 respiration to microbial biomass ratio), the ratio between microbial biomass C to total organic C ratio, and enzymatic measurements that relate to microbial biomass. The authors acknowledged that, although a SQI based on one single parameter is easy to calculate they often lack information; a limitation not much improved by using two SQ indicators. A single indicator cannot encompass all soil functions of concern; therefore, multiple-soil attributes are usually required for SQ assessment. Thus, several multi-parametric indices have been developed to obtain SQ indices that provide and integrate more information on the quality of an agricultural soil and, in a less number, for non-agricultural soils. The first multi-parametric index for the quality of agricultural soil was established by Karlen et al. (1994a). This framework uses selected soil functions, which are weighted and integrated according to the following equation:

$$SQI = qwe(wt) + qwt(wt) + qrd(wt) + qspg(wt)$$

where: qwe is the rating for accommodating water entry; qwt is the rating for water transport and absorption; qrd is the rating for resisting degradation; qspg is the rating for supporting plant growth and wt is the numerical weight for each soil function.

Glover et al. (2000) use the same SQI for apple production in conventional organic production, due to its flexibility, ease of use, and its potential for interactive use by apple producers. Their SQI uses the same soil functions, which are also weighted and integrated into a SQI equation.

Masto et al. (2007) developed this SQI a little more adding the soil functions (and their corresponding indicators) resistance to biochemical degradation, and the supply of plant nutrients and sustainability of crop productivity (in replacement of plant growth). The aim of their work was to evaluate and quantify the long-term effect of different fertilizers and farmyard manure treatments.

Andrews, Karlen, et al. (2002) were the first to compare multi-parametric methods designed to establish the quality of agricultural soils. Their work can be considered the mathematical base that many authors have followed to establish SQI for agricultural ecosystems. The SQI proposed by Andrews, Mitchell, et al. (2002) is as follows:

$$SQI = \sum 0.61 \cdot SOMi + 0.61 \cdot SEGi + 0.16 \cdot SpHi + 0.16 \cdot SWSAi + 0.15 \cdot Szni + 0.09 \cdot SBDi$$

where S is the score for the subscripted variable and the coefficients are the weighting factors derived from the PCA.

Even though SQI was proposed by Karlen et al. (1994b, 1994a) and Andrews, Karlen, et al. (2002); Andrews, Mitchell, et al. (2002) have been widely used, some authors have looked at other alternatives. Kang et al. (2005) used a trigonometric approach based on three subindices (nutritional, microbiological and crop-related) to establish a Sustainability Index. Koper & Piotrowska (2003) on their side, established a Biochemical Index of Soil Fertility to compare the effect of organic and mineral fertilization. This index classifies soil fertility in low, average, high and very high fertility categories. While physical and chemical indicators have been widely used to elaborate SQI, only a few of them have used enzymatic activity measurements despite the fact that enzymes are sensitive indicators of changes in soil In this regard, using various enzymatic activities, Puglisi et al. (2006) developed three indices of soil alteration to quantify soil deterioration caused by agricultural practices such as crop density and the use of organic fertilizers in different regions of Italy.

The assessment of SQ is, of course, of similar if not higher importance in no agricultural soils, and a few SQI have been proposed with this aim. In this regard, Amacher and collaborators proposed a new SQI for assessing forest soil health (Amacher et al., 2007), and, as previously commented, Melo Filho et al. (2007) used the methodology proposed by Karlen et al. (1994a) to assess the impact of management practices in natural forests of Brazil. Considering the effects of soil management, Burger and Kelting (1999) elaborated a soil quality index specifically for pinewoods of the species Pinus taeda, using bulk density, water table depth, N mineralization, depth aeration and biological activity as suitable soil quality indicators, applying a method like that of Karlen et al. (1994a). Bastida et al. (2006), for their part, used an approach based on Andrews, Karlen, et al. (2002) and established a Microbiological Degradation Index for natural soils in a semiarid climate. This index emphasizes the use of biochemical and carbon-related soil parameters in the establishment of the SQI, which aims to establish a threshold, below which policymakers should act to counter the negative effects that may lead to desertification in semiarid climates.

3.3.1 TOOLS FOR SOIL QUALITY QUANTIFICATION

Soil quality can be assessed using different approaches: through qualitative evaluation of soil indicators, usually done in the field, or performing analyses for quantitative measuring. Soil quality assessment tools are needed to quantify effectiveness of various management practices (Chang et al., 2022) and, for that purpose, soil characteristics are needed to evaluate soil quality, soil health and soil-based ecosystem services (Cornu et al., 2023). In recent years, several authors have reviewed extensively soil quality and soil quality assessment (Bünemann et al., 2018; Rinot et al., 2019), differentiating between analytical assessments and in-field assessment approaches; in this section, we will review, in a synthetic way, tools, protocols and databases that could be useful for those who intend to perform an assessment of soil quality or health. The web addresses cited in this section were last visited on 19/06/2024.

1. United States:

- USDA NRCS Soil Health. This program focuses on promoting soil health through sustainable practices and monitoring soil conditions https://www.nrcs.usda.gov/conservation-basics/natural-resource-concerns/soils/soil-health
- USDA NCRS Soil Quality for Environmental Health, (http://soilquality.org/home.html) provides tools for soil quality assessment like
    1. Qualitative Scorecards
    2. Field test Kits, like Soil Quality Test Kit (http://soilquality.org/tools/test_kit.html)
    3. Lab-based assessment methods
        a) Soil Management Assessment Method (SMAF). http://soilquality.org/tools/smaf_intro.html
        b) Cornell Soil Health Assessment (Comprehensive Assessment of Soil Health (CASH)) https://soilhealth.cals.cornell.edu

c) SHAPE, builds upon conceptual frameworks established by the SMAF and CASH protocols. (Nunes et al., 2021)

- USDA NRCS Web Soil Survey (WSS) provides soil data and information produced by the national Cooperative Soil Survey, useful to assess soil quality https://www.nrcs.usda.gov/resources/data-and-reports/web-soil-survey
- USDA-ARS Range Management Research Unit, Jornada Experimental Range: Land Potential Knowledge System. (Land PKS) It aims to support land managers with open-source tools that allow them to improve soil health and productivity. https://landpotential.org
- Agroecosystem Performance Assessment Tool (AEPAT): a computer program used to evaluate the agronomic and environmental performance of management practices in long-term experiments (https://catalog.data.gov/dataset/agroecosystem-performance-assessment-tool-f85eb)

2. European Union:

- European Soil Data Centre (ESDAC): Operated by the Joint Research Centre, ESDAC provides data and resources related to soil quality in Europe (https://esdac.jrc.ec.europa.eu).
- LUCAS Soil Survey: The Land Use/Cover Area frame statistical Survey (LUCAS) includes soil sampling to monitor soil quality and health across Europe (https://esdac.jrc.ec.europa.eu/projects/lucas).
- Interactive Soil Quality Assessment in Europe and China for Agricultural Productivity and Environmental Resilience (ISQAPER) aims to provide decision makers with science-based, easy to apply and cost-effective tools to manage soil quality and function. (https://www.isqaper-project.eu/)

3. France:

- GiSSOL (https://www.gissol.fr/le-gis). French soil information system to meet the demands of public authorities and society as a whole.

4. Ireland:

- Soil Quality Assessment Research Project (SQUARE): Toolbox for farmenrs to assess soil structural quality. (https://www.teagasc.ie/environment/soil/research/square/)
- Irish Soil Information System (http://gis.teagasc.ie/soils/)

5. **Netherland:**

  - National Soil Quality Monitoring Network (https://www.rivm.nl/en/node/39431)

6. **Canada:**

  - Canadian Soil Information System (CanSIS): Managed by Agriculture and Agri-Food Canada, CanSIS provides soil data and maps for soil quality assessment (https://sis.agr.gc.ca/cansis).
  - National Soil Health Strategy aims to improve soil health, promote sustainable agricultural practices and ensure environmental resilience for Canada's future (https://soilcc.ca/soilchampions/national-soil-health-strategy/).

7. **Australia:**

  - Australian Collaborative Land Evaluation Program (ACLEP): This program provides national soil data and maps for monitoring soil quality (https://www.clw.csiro.au/aclep/).
  - National Soil Research, Development, and Extension Strategy: A collaborative effort to improve soil health and quality through research and monitoring (https://www.agriculture.gov.au/agriculture-land/farm-food-drought/natural-resources/soils/national_soil_rd_and_e_strategy).
  - Soil Quality Initiative. It is the result of a collaboration between The University of Western Australia, Department of Agriculture and Food Western Australia, Grain Research and Development Corporation and South Coast Natural Resource Management. It aims to Establish benchmarked sites to identify and highlight the nature and extent of soil biological, chemical and physical constraints to production systems and to provide the basis of an ongoing soil quality monitoring and education program. https://www.soilquality.org.au/

8. **India:**

  - Soil Health Card Scheme: Launched by the Ministry of Agriculture, this program provides soil health cards to farmers, detailing soil quality and recommendations for improvement (https://soilhealth.dac.gov.in/home).

9. **Brazil:**

  - Brazilian Soil Information System (SiBS): Managed by Embrapa, this system provides soil data and maps for monitoring soil quality (https://www.dpi.inpe.br/Ambdata/English/soil_map.php).

- Brazilian Soil Spectral Service (BraSpecS http://besbbr.com.br). It can be used to predict soil attributes, such as soil texture, soil organic carbon content, and other soil quality indicators.

10. United Kingdom:

- National Soil Inventory (NSI): Managed by the Centre for Ecology & Hydrology (CEH), the NSI provides soil data for monitoring soil quality (https://www.landis.org.uk/).
- Countryside Survey: Includes soil sampling to monitor changes in soil quality across the UK (https://www.ceh.ac.uk/data/monitoring-programmes).

11. New Zealand:

- National Soils Database (NSD): Managed by Landcare Research, the NSD provides soil data for monitoring soil quality and health. (https://soils.landcareresearch.co.nz/tools/national-soils-database/nsd-development/).
- Soil Quality Monitoring Programme: Conducted by regional councils, this program monitors soil quality indicators on a regional basis (https://environment.govt.nz/assets/publications/Land-and-soil-monitoring_A_guide_for_SoE-and-regional-council-reporting.PDF).

12. South Africa:

- South Africa National Land-Cover Datasets: Provides soil data and maps for monitoring soil quality. (https://egis.environment.gov.za/sa_national_land_cover_datasets).

13. African Union:

- African Fertilizer and Soil Health Action Plan (https://au.int/sites/default/files/newsevents/workingdocuments/43470-wd-2._EN_Africa_Fertilizer_and_Soil_Health_Action_Plan_VI_170523.pdf).
- Soil Information System for Africa (Soils4Africa). (https://www.isric.org/projects/soils4africa)

14.Others:

- Biofunctool: assesses in field, quickly and synthetically, the impact of agricultural practices on soil health with a multicriteria approach (https://www.biofunctool.com/the-concept)
- Soil Navigator: A decision support system for assessing and optimizing soil functions. (http://www.soilnavigator.eu)

- Soil Health Calculator: https://github.com/jinshijian/SoilHealthCalculator (Jian et al., 2020)
- Solvita Soil Health Test: https://solvita.com/soil/

There is increasing interest in in-field assessment of soil quality. Field assessment generally does not involve special analyses, delivers immediate results, and can be easily performed by farmers, allowing self-checking and monitoring the condition of their soils and making management decision (Hughes et al., 2023). Visual soil evaluation is the most common procedure for field soil quality assessment.

In the last decades, different methods of visual evaluation of soil quality have been developed globally. Among the most widely used are the Visual Soil Assessment (VSA) (Shepherd et al., 2008), the Visual Evaluation of Soil Structure (VESS) (Ball et al., 2007; Guimarães et al., 2011), Visual Soil-Fast (McGarry, 2006), SOilPak (McKenzie, 2001), the Muencheberg Soil Quality Rating (Mueller et al., 2014), and more recently, the Cropland In-Field Soil Health Assessment (USDA, 2020). (Reviews on visual soil assessment methods: Ball et al., 2017; Bünemann et al., 2018).

All these methods visually assess parameters or indicators linked to soil quality, and some of them, such as the VSA method, also include plant quality indicators. Normally, only soil physical and biological properties are evaluated in field, although some methods, such as VS-FAST, also include measurement of some soil chemical properties (labile organic carbon or soil pH), using field-test kits (Bünemann et al., 2018). In general, the indicators assessed are very similar across these methods. The most evaluated physical and biological properties are soil structure and consistency, soil porosity, soil color, soil texture, aggregate stability, soil mottles, water infiltration, presence of tillage pan, surface ponding, biological diversity (usually earthworms' presence), root depth and rooting development, soil crusting and erosion.

Each of the indicators is given a visual score, considering the criteria or the scoring system of the method where several levels or categories are established (for example, three score levels in VSA method: poor (0), medium (1) or good (2); or 5 levels of soil structure in VSEE). Usually, the evaluation is made comparing the field sample with photographs or descriptions of the levels. Because some indicators can be relatively more important in the assessment of soil quality than others, the individual score values are usually weighted; VSA provides a x1, x2 or x3 factor depending of the relevance of the factor, and finally, an overall quality score or ranking is obtained, which indicates the state of the soil. There are available specific VSA guides for general land cover categories and for specific crops (Shepherd et al., 2008). The "Cropland in-field soil health assessment method", after the visual scores obtained informs of the risk of four main threats (compaction, soil organic matter depletion, soil organisms habitat loss or degradation and aggregate instability).

Visual field assessment methods have been proven effective enough for discriminating soil quality across different soil types and land use and management practices, in different climates (Pulido Moncada et al., 2014) and are well-suited for monitoring changes in some soil indicators (Ball et al., 2017). Close relationships between visual soil evaluations and quantitative laboratory-based soil measures have been demonstrated (Emmet-Booth et al., 2016). In this sense, Ball et al. (2017), in a study about the application, limitations and opportunities of the main visual soil assessments methods, described research results that show a close relation between measured values of soil organic carbon (C) and scores of the VSA soil C index (Cloy et al., 2015), and a positive correlation between SOM and VSA scores (especially soil color scores) (Newell-Price et al., 2013), indicating the value of this visual techniques for estimating SOC.

Field assessment of soil quality can particularly benefit from new technologies, including AI, through the development of interactive tools that can make the process easier, quicker, and more accurate. Some studies have explored the use of smartphones to predict or estimate soil properties. Many of these works are based on measuring color and analyzing images obtained with smartphone cameras to predict or estimate parameters such as SOM (Soil Organic Matter), SOC (Soil Organic Carbon), or iron content in the soil (Aitkenhead et al., 2020). In recent years, many mobile apps have been developed and made available in app stores for estimating different soil properties, although their true utility needs to be determined. Very recently, Sinclair et al. (Sinclair et al., 2024) conducted a study where they found a total of 337 apps for estimating soil properties, of which 32 were reviewed and analyzed using a rating scale that included 10 parameters (functionality, efficiency, quality, among others). One of the main conclusions of this study is the lack of functionality, of most of the apps evaluated, that they were unable to adequately identify color and quantify soil properties from captured images. In this study, the app LandPKS (https://www.landpotential.org/) stood out with the highest ratings, particularly in functionality. This app has a specific Soil Health module that allows users to track soil health of their land by visually estimating soil health indicators (according to the NRCS method of the USDA), in addition to entering basic soil data. Users are guided in the visual soil evaluation, and after introducing the scorings and some additional data, they can download their reports about their soil health. The iSQAPER app is a similar app developed by the EU Horizon-2020 project 'Interactive Soil Quality Assessment in Europe and China for Agricultural Productivity and Environmental Resilience' (iSQAPER, http://www.isqaper-project.eu/). This app, like LandPKS, guides the user in the visual determination of soil quality indicators.

3.3.2 SQI FOR MEDITERRANEAN CLIMATE AREAS

SQI tested in arid and semi-arid zones other than the Mediterranean areas are included here to expand our knowledge about their utility in the context of our project. In this sense, Sánchez-Navarro et al. (2015) state that the soil quality indicators and the resulting SQI must consider the specific ecosystem in which we operate and the soil functions we intend to preserve in general, but also those of special relevance to the experimental site. The chosen SQI must be adaptable to local or regional conditions and, therefore, the parameters needed to determine changes in soil quality, and then, the most suitable SQI, surely differ between a semi-arid wheat field in the Mediterranean and a rice paddy in tropical areas (Granatstein & Bezdicek, 1992; Jordán Vidal, 2023).

Mediterranean soils, as their name implies, are formed in areas with a Mediterranean climate. The Mediterranean climate is characterized by well-defined seasons, with rainy winters and warm summers that are generally dry. In addition to the Mediterranean Sea environment, the Mediterranean climate includes areas such as California, central Chile, South Africa (Cape region) and Western Australia (Perth).

Mediterranean soils can evolve rapidly and present different physical characteristics due to the occurrence of various processes. The first is the accumulation of organic matter, but processes of decarbonation, clay illuviation, rubefaction and pseudogleyzation also affect them (Torrent et al., 2023).

However, inadequate land management can lead to a rapid loss of soil quality with a reduction in the abundance and diversity of soil microorganisms. In this sense, agricultural land management is one of the most important anthropogenic activities that alters soil characteristics, including physical, chemical and biological properties (Burton et al., 2022; Philippot et al., 2024; T. Yang et al., 2021). On the Mediterranean coast, the main soil threats are desertification, erosion and loss of organic matter. Although some soil properties cannot be easily modified (such as texture), soil quality can be improved by implementing good management and conservation strategies. Among these strategies, the use of temporary vegetative covers and the incorporation of compost have great potential for success, if applied carefully considering the crop's water needs. These strategies provide various benefits to the agro-ecosystem, such as reducing erosion, accumulating organic matter in the soil, controlling weeds and pathogens and providing nutrients (Ding et al., 2021; Hallama et al., 2019; Kozacki et al., 2024; Martínez-Mena et al., 2020; Saquee et al., 2023).

Improving soil quality usually takes many years (it depends on the climate, the soil type and the management, for example), however, cover crops slightly improve soil quality parameters already in the first years of cultivation (Sastre et al., 2018). Soil organic carbon concentrations increase over the years in conservation management soils (no tillage), especially in the upper layers (Tedone et al., 2023).

Cover crops, especially green manures, affect the fungal composition of the soil, increasing the abundance of symbiotic soil fungi and decreasing the abundance of pathogenic fungi (Ding et al., 2021; R. Yang et al., 2023). Green manure cultivation (sole or intercropping) is an important agricultural practice that effectively increases soil fertility, soil quality, and improves the ecological environment. Green manure can conserve water and soil, reducing disease occurrence (Campanella et al., 2020; Saquee et al., 2023) and improving subsequent crop yields (Amede et al., 2021; Gao et al., 2024; Xu et al., 2023).

Applying compost (including shredded pruning wood) to agricultural land is a reliable way of improving the physical properties of most soils, especially those with poor structure and low levels of organic matter. Changes in the physical properties of soils with compost include bulk density, infiltration rate, hydraulic conductivity, water content, aggregate stability and porosity. Compacted soils have a higher bulk density and, depending on the degree of compaction, can limit root growth and water infiltration (Moraes et al., 2020; Zhang et al., 2024). Soils managed with compost and cover crops tend to increase their water infiltration capacity (higher hydraulic conductivities) and modify their porosity distribution function, resulting in a greater number of larger pores, which favors rapid water circulation at depth and aeration of the profile (Blanco-Canqui et al., 2022; Edwards et al., 2023).

The long-term application of compost to the soil improves the physical and hydrological properties and fertility of the soil (Meena et al., 2020). The application of compost increases water retention and infiltration, enhances the release of nutrients for plant uptake and reduces leaching (Suvendran et al., 2024). It also increases soil organic matter and organic carbon content through carbon fixation by plants and microbial activity (Suvendran et al., 2024). The conservation approach offers certain advantages as a long-term approach to enhance crop productivity, soil quality, and environmental effects, therefore promoting more sustainable scenarios in agricultural systems.

Andrews, Karlen, et al. (2002) describe nicely the management goals intended for vegetable production in Northern California and the soils functions supporting their achievements maintaining or improving soil fertility. In this sense, the authors selected crop productivity, water cycling and environment protections as the most significant goals that can be reached by selected physical, chemical and biological properties of the soils, namely their nutrient cycling, water availability, soil stability and support, filtering and buffering capacity, soil resistance and resilience and, finally, biodiversity abundance. This list of properties led to the elaboration of an easy SQI following the additive model based on 7 indicators: pH, mineralizable N (or alternatively microbial mass Carbon), aggregate stability, bulk density, available water capacity, electrical conductivity and Na absorption ratio, the last two of special interest in arid zones.

Sánchez-Navarro et al. (2015) found out that different statistical analyses are useful for selecting the most appropriate indicators for Mediterranean semi-arid soils. The SQI based on the selected indicators explained about 80% of the accumulated variance, with porosity and water availability as the most sensitive physical indicators for the ecosystems, while organic carbon and K+ contents were the most sensitive chemical indicators.

Working with soils under semiarid conditions in Spain, Zornoza et al. (2007); Zornoza, Mataix-Solera, et al. (2008) established and tested two equations using multilinear regression systems focusing on evaluating the environmental quality of soils under natural vegetation. The first equation established a correlation between nitrogen and various enzyme activity and physico-chemical metrics, which applies to Mollisols. The second defined soil organic carbon using comparable indicators and is applicable to Entisols.

More recently, Raiesi (2017) assessed long-term crop cultivation effects on soil quality index (SQI) in rangelands of western Iran and determined that organic carbon and salinity were the key indicators of soil changes in a region where long-term cultivation has severely degraded SQ in native rangelands, limiting crop productivity to 52–64% of their potential capacity.

In summary, the above information describes the different procedures that can be followed to measure SQ establishing SQI based on selected soil quality indicators in agricultural and no agricultural soils, focusing especially in Mediterranean and other arid and semi-arid zones of the planet. As Bastida et al. (2008) state physical and chemical soil properties are more often included than biological parameters in the calculation of SQI, despite that biological changes can be more sensitive and precede perceived changes in SQ. Therefore, we suggest a more ample use of biological soil properties, especially of those more related with the capacity of the soil to function as a C sink and the management techniques improving them (S. Li et al., 2016).

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4 SOIL CARBON SEQUESTRATION MODELS

4.1 Introduction

The complex array of living organisms known as soil organic matter (SOM) includes fungi, bacteria, and various phases of decomposition of plant and animal residue. It also includes humus, a stable substance that bears little resemblance to the organisms from which it is derived. SOM's composition is dominated by carbon (C), hydrogen, and oxygen, with minor amounts of nitrogen, phosphorus, and sulfur. This is because SOM originates from living tissues. The concentration of soil organic carbon (SOC) in grams per kilogram or mass per hectare (g/ha) to a specific depth expresses the levels of SOM. When net atmospheric CO2 removal is accomplished i.e. when C inputs (non-harvestable net primary productivity) exceed C outputs (soil respiration, C expenses associated with fossil fuels and fertilizers), carbon sequestration takes place in managed soils. An added benefit of soil C sequestration is that all of its methods adhere to sustainable agriculture principles (e.g., reduced tillage, erosion management, diversified cropping systems, enhanced soil fertility).

More than ever, soil organic matter models are now utilized to extrapolate our knowledge of SOM dynamics over time and space, allowing us to evaluate C fluxes from entire regions or continents. Numerous research works have implemented techniques to evaluate SOM dynamics on a regional, national, and international level (Le Noë et al., 2023). Policy makers at the national, regional, and international levels are increasingly using soil organic matter models, as seen in the post-Kyoto discussion over the terrestrial biosphere's capacity to store carbon. Our existing SOM models continue to encompass a range of theories and levels of understanding. Future advancements in SOM models will deepen our comprehension and enable the adoption of truly predictive models—one that does not require site-specific calibration. These advancements will lower the uncertainty surrounding SOM model predictions and enhance its estimations.

4.2 Literature review on SOC modelling

A thorough review of SOC modelling was carried out based on recent meta-analysis reviews, published in the relevant literature (De Rosa et al., 2024; Le Noë et al., 2023; Tadiello et al, 2023). Our understanding of the environmental and management controls of soil carbon sequestration in agricultural environments has improved as a result of the thorough descriptions of experimental data. The rate and extent of soil C sequestration are primarily determined by the amount and quality of C entering the soil and how that C interacts with the soil biophysical environment. It has been demonstrated that the amount of C that is incorporated into the soil through organic amendments, crop residues, and roots influences the course of SOC over time. It is almost certain that management techniques aimed at maximizing nutrient availability and establishing nutrient reserves—such as fertilization and crop rotation with legumes—will increase soil C stocks. Crop residue quality and the time of its soil integration both affect the decomposition of carbon and, consequently, the storage of carbon in the soil.

The extent of soil disturbance plays a significant role in controlling the decomposition and retention of C in soil by influencing soil aggregation. Given this, one of the most important technological advances of the past 30 years has been no-tillage agriculture, which enables farmers to raise crops profitably while lowering erosion and enhancing the quality and quantity of soil organic matter. Numerous models depicting the dynamics of SOC have been created since the early 1930s for a range of temporal and spatial scales, climatic conditions, land uses, and land cover. The SOC models that are more frequently seen in the literature are process-based, since they concentrate on the physical mechanisms that govern the movement and changes of biological matter.

4.2.1 PROCESS-BASED MODELS

Process-based models are based on conceptual SOC pools that decay following first order kinetics and consider biogeochemical processes that rely on mathematical-ecological theory. They have the ability to simulate SOC turnover and at some cases relate it to management practices. They are established at various temporal and spatial scales based on scenarios that characterize intra and inter-annual dynamics of SOC. Process-based models are multi-compartment models i.e. they partition the total SOC mass into specific pools. Early modelling approaches treated SOM as one homogeneous compartment, but with the perpetual increase in computational power, multi-compartment models are continuously being developed. Most of process-based SOM models currently found in the literature are multi-compartment models (Table 4.2).

The position of each compartment in a model and its rate of decay define the compartment's characteristics. Decay rates are usually expressed by first-order kinetics with respect to the concentration (C) of the pool i.e. $dC/dt = - kC$, where t is the time. The rate constant k of first-order kinetics is related to the time required to reduce by half the concentration of the pool, without additional inputs. According to first-order kinetics, decay rates are closely associated with the SOC stocks of the several pools taken into account. Rate modifiers show that significant variables, such as soil temperature, soil moisture content, and clay content, affect microbial and physical processes. Two major categories of multi-compartment, process-based models can be identified in the literature, based on the representation of SOC decomposition kinetics:

1. Process-based models relying only on conceptual SOC pools, where SOC decaying usually follows first order kinetics. The majority of models appearing in Table 1, are first order models (e.g. RothC)

2. Process-based models combining microbial and physical processes controlling SOC decaying and stabilization by describing enzymatic reactions, diffusion and/or sorption kinetics (non-linear). The models that follow the non-linear SOC decay are marked with an asterisk in Table 1. In this category, non-linear kinetics consider the feedback between microbial activity and SOC substrates by representing the decay rate as a function of SOC and/or microbial C stocks (Georgiou et al., 2023; Wieder et al., 2013). Literature review has revealed that up until 2000 the appearance of non-linear kinetics in SOC modelling was limited. One possible explanation for the recent rise in literature references of SOC models based on nonlinear kinetics is that these models enable us to consider the transient dynamics and feedback reactions of soil microorganisms to changing environments and SOC decomposition. Even though linear models don't always accurately depict these effects, their inherent stability and simplicity renders them as the preferred choice. The necessity to account for nonlinear effects in the context of climate change has increased the use of nonlinear models within the past ten years. Therefore, nonlinear models are still predominantly constructed exclusively for smaller scales, reflecting the geographical scales at which the necessary data are available. Furthermore, local-scale rather than global-scale data will be required for models to provide decision-support to improve SOC sequestration at the plot or farm level.

4.2.1.1 Rothamsted Carbon Model (RothC)

In the category of first-order models, the Rothamsted Carbon Model (RothC) model is one of the most commonly used models in SOC modelling. RothC is a model of C dynamics in non-water-logged soils, initially developed to model C turnover in arable soils. It takes into consideration the effects of temperature, moisture content and soil type, using a monthly step for calculations. SOC is divided into five compartments or pools, depending on the rate of decomposition: inert organic matter (IOM), easily decomposable plant material (DPM), resistant plant material (RPM), microbial biomass (BIO) and humified organic matter (HUM). The IOM pool resists decomposition and does not receive C inputs. All compartments except IOM decompose following first-order processes. The model structure is displayed in Figure 4.1.

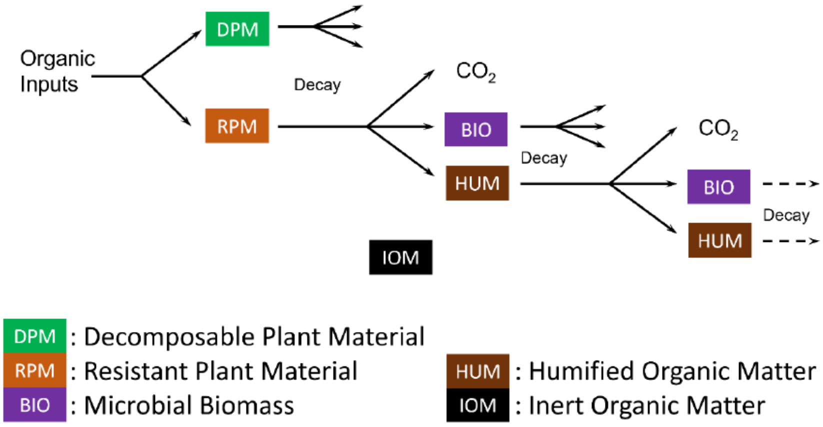

Figure 4.1. RothC model multi-department structure

Carbon from incoming plant inputs is split between DPM and RPM, depending on the DPM/RPM (decomposability) ratio of the particular incoming plant material. For most agricultural crops, a DPM/RPM ratio of 1.44 is used i.e., 59% of the plant material is DPM and 41% is RPM. All incoming plant material enters these two compartments only once. Both DPM and RPM decompose to form CO2, BIO and HUM. The proportion that goes to CO2 and to BIO + HUM is determined by the clay content of the soil. The BIO + HUM is then split into 46% BIO and 54% HUM. BIO and HUM both decompose to form more CO2, BIO and HUM. Farmyard manure is assumed to be more decomposed than normal crop plant material. It is split in the following way: DPM 49%, RPM 49% and HUM 2%.

RothC has been applied across several ecosystems, climate conditions, and land use (LU) classes using data from long-term experiments (Arnell et al., 2013; Liu et al., 2011). Farina et al. (2013) modified the soil water dynamics for semi-arid regions, and Giongo et al. (2020) created a daily version and modified the soil water dynamics, for Caatinga shrublands, in the semiarid region, North-East Brazil. The data requirements for using RothC to generate simulations are listed in Table 4.1.

Table 4.1. RothC data requirements

	Input Data / parameters
1	Monthly rainfall (mm).
2	Monthly open pan evaporation (mm). Monthly potential evapotranspiration can be used divided by 0.75
3	Average monthly mean air temperature (°C).
4	Soil clay content (%).
5	Decomposability of the incoming plant material i.e. DPM/RPM ratio.

6	Soil cover; specify the presence or absence of vegetation in the ground surface.
7	Monthly input of plant residues (t C ha^{-1}). Carbon that enters the soil per month (t C ha^{-1}), including carbon released from roots during crop growth.
8	Monthly input of farmyard manure (FYM) (t C ha^{-1}), if any. FYM follows a different treatment from inputs of fresh plant residues.
9	Depth of soil layer sampled (cm)

A wide range of soil and climate attributes for which data are lacking can be filled in using predictive functions. PET can be estimated from simple models using temperature alone, models based on solar radiation, or "combined" models requiring an array of climate variables (Maas et al., 2023). Numerous environmental variables, including air temperature and humidity, precipitation, wind speed, and sun radiation, can be entered into PET computations.

Additionally, proxy data such as field coverage by vegetation, and biomass or yield production, can be obtained by remote sensing (RS). This data can be used to calculate the amount of C that a system's roots and surface litter add to the soil – a critical component of RothC model. Despite their abundance, crop yield estimation models often capture only a specific crop type and cannot easily provide temporal-continuous information for the entire agricultural production (Neumann et al., 2018). The total assimilated C via photosynthesis is the Gross Primary Production (GPP). About half of GPP is soon released to the atmosphere via autotrophic respiration. The remaining part, the Net Primary Production (NPP), is allocated into compartments with a longer residence time such as leaves, roots or other structures. An EO-data model using satellite remote sensing information and capturing all land cover types worldwide is MOD17, which provides productivity information since the year 2000 at 1-km resolution (Zhao and Running, 2010).

The wide acceptance and applicability of RothC as identified in the literature, is mostly related to the simplicity of the models' conceptual design. In comparison, CENTURY has a broader modelling scope than RothC, including C, N, phosphorus and also sulfur dynamics. This results in a higher number of variables/parameters required for model formulation. The lower number of required input data makes RothC more easily applicable in the spatial context, with lower computational cost than CENTURY or even more complex models. However, because RothC fails to represent some biological processes, its simplicity comes with an associated cost. The RothC model was tested against measurements from 16 long-term experimental sites across global croplands more recently, using the model's original default parameters. The results indicated that the model performed generally well in representing the SOC dynamics under different conditions across multiple sites. (Wang et al., 2016).

Table 4.2. Multi-compartment, process-based SOC models (non-linear models designated with asterisk)

1.	AMG	Saffih-Hdadi, K. & Mary, B. Modeling consequences of straw residues export on soil organic carbon. Soil Biol. Biochem. 40, 594–607 (2008).
2.	ANIMO	Rijtema, P.E.; Kroes, J.G. Some results of nitrogen simulations with the model ANIMO. Fert. Res. 1991, 27, 189–198.
3.	APSIM	McCown, R.L.; Hammer, G.L.; Hargreaves, J.N.G.; Holzworth, D.P.; Freebairn, D.M. APSIM: a novel software system for model development, model testing and simulation in agricultural systems research. Agr. Syst. 1996, 50, 255–271.
4.	* BACWAVE -WEB5	Zelenev, V. V., van Bruggen, A. H. C., Leffelaar, P. A., Bloem, J. & Semenov, A. M. Oscillating dynamics of bacterial populations and their predators in response to fresh organic matter added to soil: The simulation model 'BACWAVE-WEB'. Soil Biol. Biochem. 38, 1690–1711 (2006).
5.	Candy	Franko, U. Modelling approaches soil organic matter turnover within the CANDY system. In Evaluation of Soil Organic Matter Models Using Existing, Long-Term Datasets; NATO ASI I38; Powlson, D.S., Smith, P., Smith, J.U., Eds.; Springer-Verlag: Berlin, 1996; 247–254.
6.	CASA-CNP	Jian, J. et al. Leveraging observed soil heterotrophic respiration fluxes as a novel constraint on global-scale models. Glob. Change Biol. 27, 5392–5403 (2021).
7.	CENTURY	Parton, W.J.; Stewart, J.W.B.; Cole, C.V. Dynamics of C, N, P, and S in grassland soils: a model. Biogeochem- istry 1987, 5, 109–131.
8.	CIPM	Kuka, K., Franko, U. & Rühlmann, J. Modelling the impact of pore space distribution on carbon turnover. Ecol. Model. 208, 295–306 (2007).
9.	CN-SIM	Petersen, B. M. et al. CN-SIM: a model for the turnover of soil organic matter. II. Short-term carbon and nitrogen development. Soil Biol. Biochem. 37, 375–393 (2005).
10.	* CORPSE	Jian, J. et al. Leveraging observed soil heterotrophic respiration fluxes as a novel constraint on global-scale models. Glob. Change Biol. 27, 5392–5403 (2021).
11.	DAISY	Laub, M. et al. DRIFTS band areas as measured pool size proxy to reduce parameter uncertainty in soil organic matter models. Biogeosciences 17, 1393–1413 (2020).
12.	DNDC	Li, C.; Frolking, S.; Harriss, R. Modelling carbon biogeochemistry in agricultural soils. Global Biogeochem. Cycles 1994, 8, 237–254.
13.	DSSAT	Cycles 1994, 8, 237–254. Hoogenboom, G.; Jones, J.W.; Hunt, L.A.; Thornton, P.K.; Tsuji, G.Y. An Integrated Decision Support System for

	Crop Model Applications, Paper 94-3025, ASAE Meeting, Missouri, June 1994; 23 pp.
14. D3R	Douglas, C.L., Jr.; Rickman, R.W. Estimating crop residue decomposition from air temperature, initial nitrogen content, and residue placement. Soil Sci. Soc. Am. J. 1992, 56, 272–278.
15. * Ecosys	Grant, R. Modeling transformations of soil organic carbon and nitrogen at differing scales of complexity. Modeling carbon and nitrogen dynamics for soil management (2001).
16. EPIC	Williams, J.R. The erosion-productivity impact calculator (EPIC) model: a case history. Phil. Trans. Roy. Soc. Lond. B 1990, 329, 421–428.
17. FERT	Lond. B 1990, 329, 421–428. Kan, N.A.; Kan, E.E. Simulation model of soil fertility. Physiol. Biochem. Cultivated Plants 1991, 23, 3–16.
18. ForClim-D	Perruchoud, D.O. Modeling the Dynamic of Non-living Organic Carbon in a Changing Climate: A Case Study for Temperate Forests. Ph.D., Thesis, ETH Diss. No. 11900, 1996; 196 pp.
19. GENDEC	Moorhead, D.L.; Reynolds, J.F. A general model of litter decomposition in the northern Chihuahuan desert. Ecol. Model. 1991, 56, 197–219.
20 HPM/EFM	Thornley, J.H.M.; Verberne, E.L.J. A model of nitrogen flows in grassland. Plant Cell Environ. 1989, 12, 863–886.
21. ICBM	Andrén, O.; Kätterer, T. ICBM—the introductory carbon balance model for exploration of soil carbon balances. Ecol. Appl. 1997, 7, 1226–1236.
22 KLIMAT-SOIL-YIELD	Sirotenko, O.D. The USSR climate–soil–yield simulation system. Meteorologia i Gidrologia 1991, 4, 67–73.
23 LPJ	Sitch, S. et al. Evaluation of ecosystem dynamics, plant geography and terrestrial carbon cycling in the LPJ dynamic global vegetation model: LPJ dynamic global vegetation model. Glob. Change Biol. 9, 161–185 (2003).
24 Humus balance	Schevtsova, L.K.; Mikhailov, B.G. Control of Soil Humus Balance Based on Statistical Analysis of Long-Term Field Experiments Database; VIUA: Moscow, 1992, (in Russian).
25 * MIMICS	Wieder, W. R. et al. Explicitly representing soil microbial processes in Earth system models: Soil microbes in earth system models. Glob. Biogeochem. Cycles 29, 1782–1800 (2015).
26 MOMOS	Pansu, M., Bottner, P., Sarmiento, L. & Metselaar, K. Comparison of five soil organic matter decomposition models using data from a 14 C and 15 N labeling field experiment: Comparison of five soil organic matter models. Glob. Biogeochem. Cycles 18, n/a–n/a (2004).

27 MOTOR	Whitmore, A.P.; Klein-Gunnewiek, H.; Crocker, G.J.; Klír, J.; Körschens, M.; Poulton, P.R. Simulating trends in soil organic carbon in long-term experiments using the Verberne=MOTOR model. Geoderma 1997, 81, 137–151.
28 N14CP-Agri	16, Janes-Bassett, V., Davies, J., Rowe, E. C. & Tipping, E. Simulating long-term carbon nitrogen and phosphorus biogeochemical cycling in agricultural environments. Sci. Total Environ. 714, 136599 (2020).
29 NAM SOM	Ryzhova, I.M. Analysis of sensitivity of soil-vegetation systems to variations in carbon turnover parameters based on a mathematical model. Eurasian Soil Sci1993, 25, 43–50.
30 NCSOIL	Molina, J.A.E.; Hadas, A.; Clapp, C.E. Computer simulation of nitrogen turnover in soil and priming effect. Soil Biol. Biochem. 1990, 22, 349–353.
31. NICCE	Van Dam, D.; Van Breemen, N. NICCE—a model for cycling of nitrogen and carbon isotopes in coniferous forest ecosystems. Ecol. Model. 1995, 79, 255–275.
32 O'Brien model	O'Brien, B.J. Soil organic carbon fluxes and turnover rates estimated from radiocarbon measurements. Soil Biol. Biochem. 1984, 16, 115–120.
33 ORCHIDEE-PRIM	Guenet, B. et al. Impact of priming on global soil carbon stocks. Glob. Change Biol. 24, 1873–1883 (2018).
34 Q-soil	Bosatta, E.; Ågren, G.I. Theoretical analyses of the interactions between inorganic nitrogen and soil organic matter. Eur. J. Soil Sci. 1995, 76, 109–114.
35 PRIM	Guenet, B., Moyano, F. E., Peylin, P., Ciais, P. & Janssens, I. A. Towards a representation of priming on soil carbon decomposition in the global land biosphere model ORCHIDEE (version 1.9.5.2). Geosci. Model Dev. 9, 841–855 (2016).
36 RothC	Coleman, K.; Jenkinson, D.S.; Crocker, G.J.; Grace, P.R.; Klír, J.; Körschens, M.; Poulton, P.R.; Richter, D.D. Simulating trends in soil organic carbon in long-term experiments using RothC-23.6. Geoderma 1997, 81, 29–44.
37 SOCRATES	Grace, P.R.; Ladd, J.N. SOCRATES v2.00 User Manual; Co-operative Research Centre for Soil and Land Management: Glen Osmond, South Australia, 1995.
38 * SOMKO	Gignoux, J. et al. Design and test of a generic cohort model of soil organic matter decomposition: the SOMKO model: SOMKO: a generic decomposition model. Glob. Ecol. Biogeogr. 10, 639–660 (2001).
39 SOMM	Chertov, O.G.; Komarov, A.S. SOMM—a model of soil organic matter and nitrogen dynamics in terrestrial ecosystems. In Evaluation of Soil

	Organic Matter Models Using Existing, Long-Term Datasets; Powlson, D.S., Smith, P., Smith, J.U., Eds.; NATO ASI I38; Springer- Verlag: Berlin, 1996; 231–236.
40 Sundial	Smith, J.U.; Bradbury, M.J.; Addiscott, T.M. SUNDIAL: simulation of nitrogen dynamics in arable land. A user-friendly, PC-based version of the Rothamsted nitrogen turnover model. Agron. J. 1996, 88, 38–43.
41. Verberne	Verberne, E.L.J.; Hassink, J.; de Willigen, P.; Groot, J.R.R.; van Veen, J.A. Modelling soil organic matter dynamics in different soils. Neth. J. Agric. Sci. 1990, 38, 221–238.
42 Yasso	24, Mao, Z. et al. Modeling soil organic carbon dynamics in temperate forests with Yasso07. Biogeosciences 16, 1955–1973 (2019).

4.2.1.1 *Process-based models' validation*

Process-based models, particularly those that incorporate both physical and microbiological processes, tend to become more complex and incorporate an increasing number of bio-geochemical processes. However, including more processes or compartments in SOC models, over-fitting of the model parameters becomes possible and may lead to undesirable biases. Despite the numerous model applications found in literature, there seems to be no consensus on any approach for understanding and predicting SOC dynamics. As a consequence of the wide range of approaches, large disparities in predicted SOC values are observed among models, regardless of model category or temporal and spatial scales, suggesting the need for more thorough SOC model validation processes. The lack of standardization in the model validation criteria, further complicates the comparison of model performance.

Validation of models is a critical step to improve confidence in SOC model predictions. In a comprehensive evaluation of SOM models, Izaurralde et al., 2001 tested nine models against data sets from seven long-term experiments and the results showed that specific models – including RothC - had significantly lower overall errors [root mean square error (RMSE)], than other models. Wang et al. (2016) used data from 16 long-term experimental sites spread around the wheat-growing regions of the world to assess the model's efficiency in simulating fluctuations in soil C. According to the verified results, the model could fairly replicate the dynamics of soil organic matter across a broad spectrum of climatic and soil conditions as well as agricultural management practices.

Typically, the more data that is gathered regarding SOC stocks and SOC compartments, bulk density in vertical SOC profile, moisture content, clay content, C inputs from plants, microbial biomass, etc., the more reliable the model outputs will be. Long-term field experiments, in particular, offer insightful empirical insights for assessing SOC models. The decadal field experiments, which are now in place and offer long-term time-series data on SOC stocks under various climatic circumstances, constitute a useful source of data given the time and resources needed to build high value long-term data sets and monitoring networks.

The diversity in SOC modelling approaches can be helpful in improving the prediction ability for SOC stocks. Model diversity is a fundamental characteristic in the case of multi-model ensemble approaches (Riggers et al., 2019; Farina et al., 2021). Implementing weighted averages and selecting models based on performance criteria can decrease prediction error and enhance the reliability of predictions, compared to simulations using a single model. Still, in multi-model ensemble approaches, standardizing approaches to modeling is a crucial problem; model inter-comparisons are challenging due to the selection of calibrating parameters, initialization strategies for different soil compartments, and forcing variable estimation. Nevertheless, multi-model ensembles appear promising, offering higher reliability than single models.

4.2.2 STATISTICAL MODELS (DATA-DRIVEN)

Despite the continuous development of process-based models, upscaling the results from such models is constrained by several factors, mainly because of the lack of spatial data at the required spatiotemporal resolution, particularly on soil properties. Alternatively, the digital soil mapping framework of the SCORPAN regression kriging approach has been used to model the spatial and temporal distribution of soil carbon at larger scales (Stockmann et al., 2015). Using this approach, a collection of global environmental covariates is assembled, selected to reflect a variety of soil-forming factors and soil-change drivers, including digital elevation models and their derivatives, climate data (long-term precipitation and temperature data), land-cover data and EO-data based biophysical indicators. Such environmental covariates or predictors, available over areas of interest can be used to generate spatial predictions of soil carbon, by modelling the relationship between target and auxiliary environmental variables. In a parallel manner, the research in digital soil mapping based on various machine and deep learning methods is ongoing. (Radočaj et al., 2024) Decision trees, such as Random Forest (RF), Gradient Boosting Machines (GBM), Cubist, and Quantile Random Forest (QRF), are the most prevalent machine learning methods used for total soil carbon prediction. Random Forest (RF) and Gradient Boosting Machines (GBM) are often used to construct ensemble decision trees. They combine several weak learners to generate a strong learner, which is a key component of the supervised learning strategy. (Radočaj et al., 2024).

In statistical, data-driven spatio-temporal carbon modelling the crucial data besides the available spatial covariates are point observations – preferably repeated - with standardized measurements of SOC concentrations or stocks. De Rosa et al., 2024 employed a data-driven spatial SOC changes modelling approach, utilizing SOC temporal change data obtained from the Land-Use/Land-Cover Area Frame-

Survey (LUCAS) conducted across EU member states in 2009, 2015 and 2018. This novel approach provided for the first time an estimate of SOC changes at the European Level, using quantile generalized additive modelling (qGAM) and LUCAS revisited points. qGAMs are non-parametric regression models that demonstrate the capacity to capture the non-linear correlation between the response and explanatory variables using smooth effects. No previous hypotheses regarding the conditional distribution of the conditional response variable are necessary. This enhances the robustness of qGAMs when the variance of the response variable varies in relation to the explanatory variables.

4.3 SOC modelling applications

4.3.1 PROCESS-BASED MODELS

The RothC carbon model was used to spatio-temporally simulate the soil C dynamics in croplands, for a time span of 10 years, during 2009-2018. The study area is in northern Greece, covering 140K ha of agricultural land with wheat, barley, maize and several other crops. The masking of the agricultural land cover was based on Copernicus Land Monitoring Service (ver.3). Land Cover Change Version 3.0 product at 100 m resolution (Figure 4.2).

The RothC model has been frequently and extensively implemented to simulate changes in soil carbon under a variety of soil-climate conditions and management practices in agricultural systems worldwide. These assessments typically rely on the consideration of relatively large areas as homogeneous in terms of the response of soils to land use change or to variation in climatic variables like temperature and precipitation. In the current approach, RothC application is spatially explicit, i.e. cell-based to take advantage of EO-data and their spatial and temporal variability to spatio-temporally simulate the Soil-C dynamics in croplands. EO-data were assessed through GEE platform, and spatial modelling and processing was implemented in R computational environment. RothC modelling was implemented with a differential equations approach, using the package SoilR (Sierra et al., 2012).

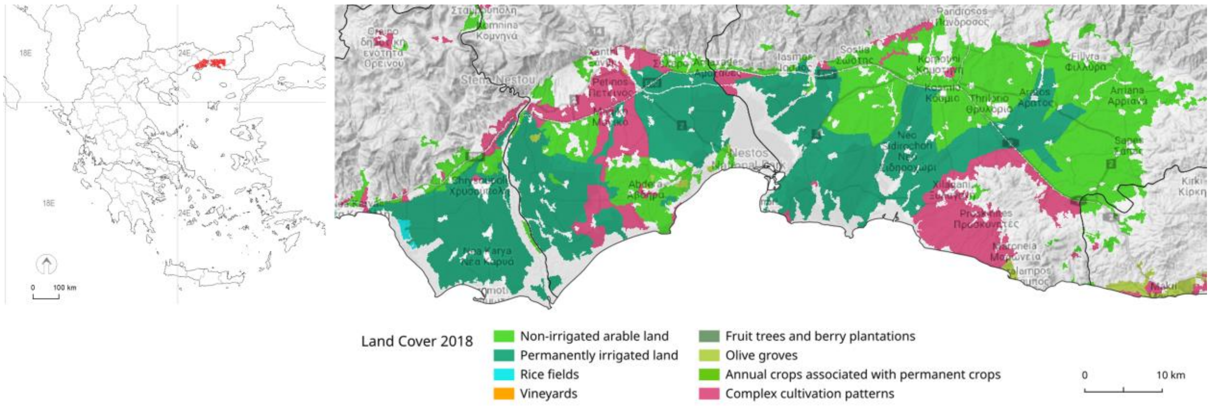

Figure 4.2. Agricultural LC mask

The application of RothC model was based on geographical data, mainly from public-access geospatial information concerning land cover, soil, climate, and productivity from both online and local sources:

4.3.1.1 Land Cover data

Copernicus Land Monitoring Service (ver.3). Land Cover Change Version 3.0 product at 100 m resolution. The Copernicus Global Land Service (CGLS) generates a series of qualified bio-geophysical products regularly, at global scales with medium to low spatial resolution (https://land.copernicus.eu/global/products/lc). Land cover from CGLS was used for the purpose of masking the area of interest to the agricultural land cover class.

4.3.1.2 Soil data

The Regional Soil Mapping survey, carried out during 2008-2009 was the source of available soil data, including 362 soil profiles with analytical data in several layers up to 1m (Figure 4.3).

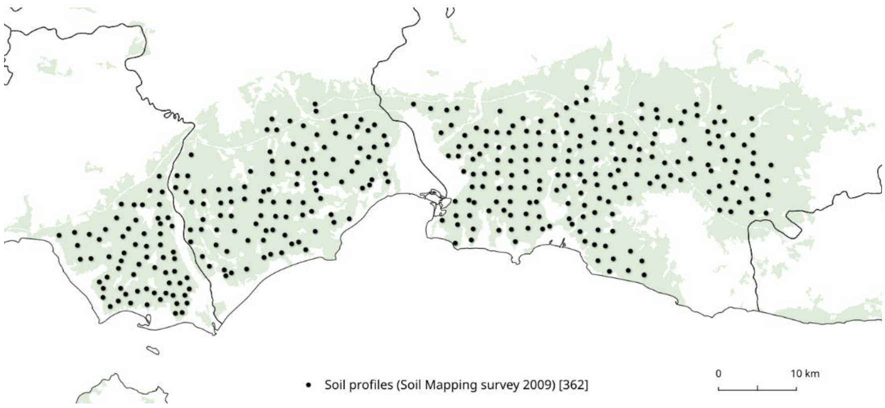

Figure 4.3. Soil profiles from 2008-2009 Regional Soil Mapping survey

Spatial predictions from geostatistical models, build from the top layers of the distribution of soil profiles, concerning Soil bulk density, Clay Soil fraction and Initial Carbon concentration, were generated with a spatial resolution of 250m. The resulting distributions are displayed in Figure 4.4 and Table 4.3. RothC simulates carbon dynamics in terms of carbon density (ton C ha^{-1}) which is referred commonly as carbon stock per area unit. Initial soil carbon concentrations SOC (%) are transformed into stocks SCD (t ha^{-1}) using the formula

$$SCD = SOC * BD * d * (1-(frag/100))$$

Where BD = bulk density (g/cm^3), d = soil depth (cm), frag = vol. of coarse fragments %

Table 4.3. Input data statistics

AOI: input statistics (n=22550)									
Variable	units	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	sd	CV
Soil bulk density	g/cm^3	10.28	24.74	27.94	28.36	31.78	51.63	5.367	18.93
Clay Soil fraction	%	22.45	29.61	31.07	31.15	32.7	41.23	2.351	7.547
Initial Carbon Stock	t/ha	24.37	26.54	27.85	28.11	29.76	34	1.829	6.509

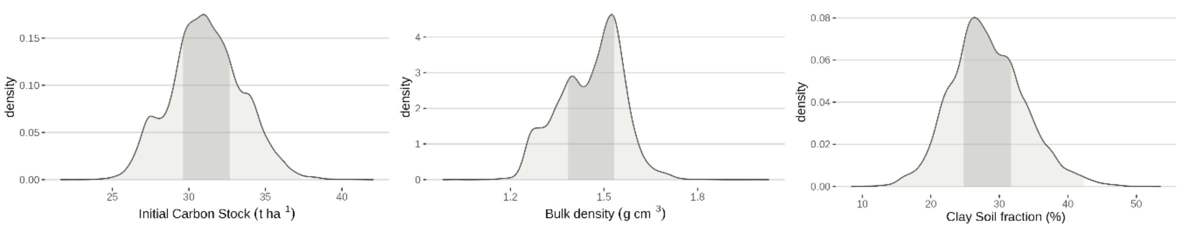

Figure 4.4. Input data distributions

4.3.1.3 Climate data

Climate Data Store - European Centre for Medium-Range Weather Forecasts (ECMWF) produces global data regarding the land component of the European Re-Analysis (ERA5), referred to as ERA5-Land (https://developers.google.com/earth-engine/datasets/catalog/ECMWF_ERA5..). Climatic data concerning temperature, precipitation, and evapotranspiration as monthly averages, were accessed in the form of time-series averages for the time period of 2009–2018. The resulting distributions are displayed in Figure 4.5.

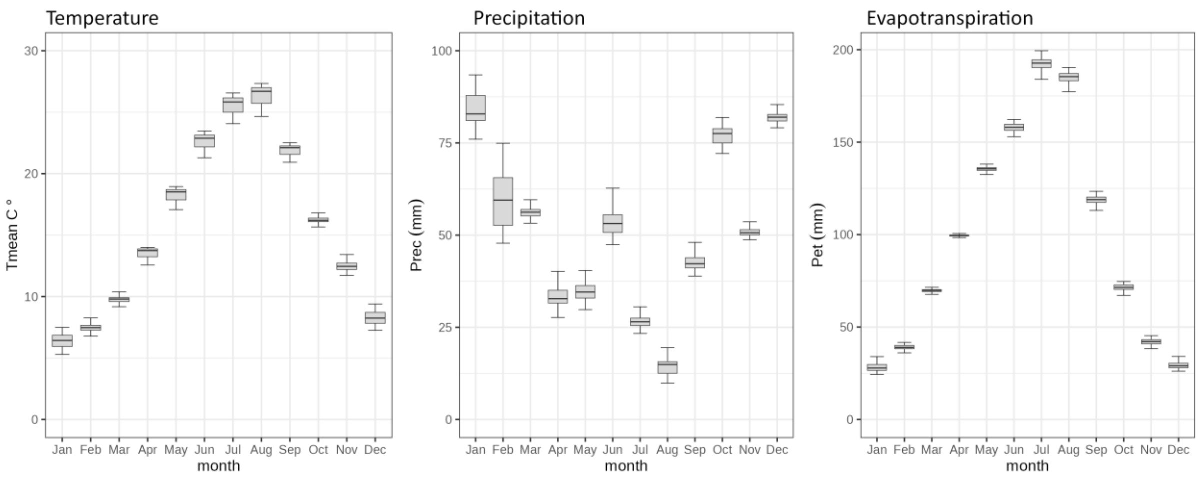

Figure 4.5. Climate data monthly distributions

4.3.1.1 Productivity data

Carbon inputs originate from crop residues, roots and manure (Wang et al., 2017). The latter is expressed in RothC as separate input (FYM) from residues and roots, and in absence of any relevant information is considered as zero input, allowing the use of EO-based productivity data for the estimation of C-input on a monthly basis.

MODIS data allows estimation of plant productivity using the MOD17 algorithm (Zhao and Running, 2010), which uses biogeochemical principles on daily climate input, providing annual NPP and GPP (Net and Gross Primary Production). The yearly product at 500m resolution (https://developers.google.com/earth-engine/datasets/catalog/MODIS_061_MOD17A3HGF) (Running S., Zhao M. 2021) was extracted for the decade of interest (2009-2018), resulting in the distribution displayed in Figure 4.6. NPP comprises all C allocated into plant compartments (above- or belowground, stem or leaves). Following the approach by Neumann M., 2018, we considered three proportions of NPP: roots 22%, aboveground residues 40% and harvested material 38%.

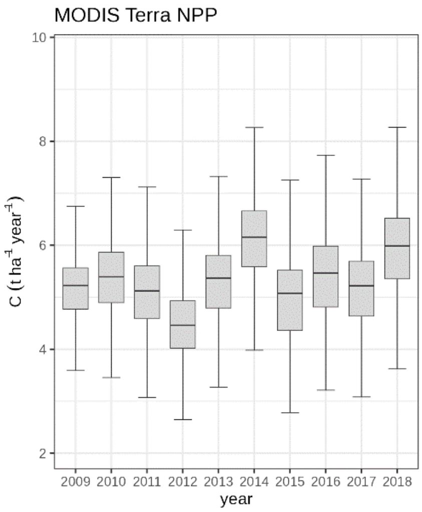

Figure 4.6. MODIS NPP distributions (2009-2018)

4.3.1.2 Model initialization

RothC model uses five conceptual pools (Figure 1) for SOC modelling, including two litter-driven compartments (decomposable plant material, DPM, and resistant plant material, RPM) and three more pools, namely microbial biomass (BIO), humified organic matter (HUM) and inert organic matter (IOM). These carbon pools must be explicitly defined during model initialization, since they are purely conceptual, regardless the fact that they are difficult to quantify on regional to continental scales. As a solution the model could be run into equilibrium mode, matching a given SOC content, which is a time consuming and complex process, requiring additional data, such as historical climate data and uncertain information about the carbon input from plant residues and/or manure application. Weihermülleret al., 2013, developed pedotransfer functions (PTFs) based on soil organic carbon (SOC) and clay content data to predict all active carbon pools of the RothC model.

$$RPM = (0.1847 \cdot SOC + 0.1555) \cdot (clay + 1.2750) - 0.1158,$$

$$HUM = (0.7148 \cdot SOC + 0.5069) \cdot (clay + 0.3421)\ 0.0184,$$

$$BIO = (0.0140 \cdot SOC + 0.0075) \cdot (clay + 8.8473)\ 0.0567,$$

where SOC is expressed in t ha^{-1} and clay in % mass. Additionally, IOM that represents a small, stable, and biologically-inert fraction of soil carbon, was estimated by PTFs developed from long-term experiments by Falloon et al., 1998. The DPM fraction is subsequently estimated using the Falloon method

$$IOM = 0.049 \cdot SOC1.139,$$

$$DPM = SOC – IOM – RPM – HUM - BIO$$

4.3.1.1 Results

RothC simulation results reveal a general SOC increase over time in the study area with a mean value of 3.7 t C ha^{-1}. Statistics for the resulting distribution are presented in Table 4.4. RothC simulation statistics. The final simulation result for the end of the time period of 2009-2018 is displayed in Figure 4.7. The quantified SOC stock changes also showed large spatial disparities across the study area, with the smallest increase and minor decrease appearing in specific regions in the eastern part of the area. These spatial patterns are directly related to the spatial heterogeneity of the NPP input data, that is characteristic and consistent throughout the entire decade 2009-2018 (Figure 4.8).

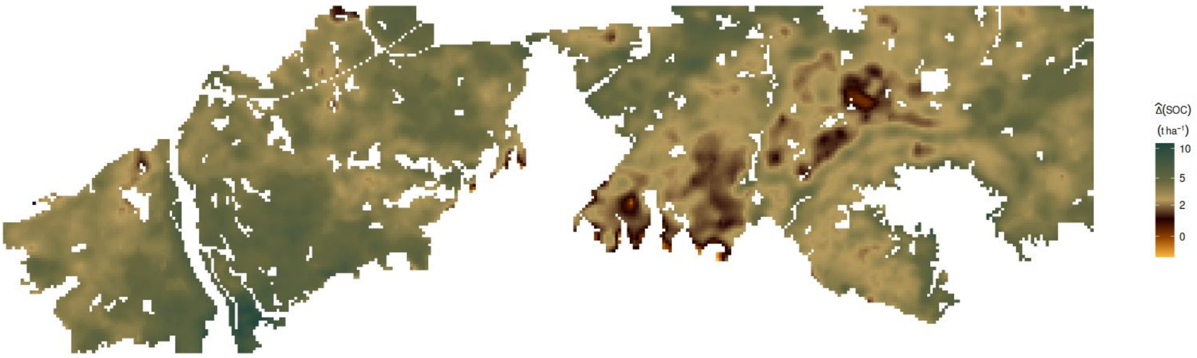

Figure 4.7. RothC simulation of C-dynamics (2018)

Table 4.4. RothC simulation statistics

AOI: RothC statistics (n=22550) – 2018 simulation							
variable	**units**	**Min.**	**1st Qu.**	**Median**	**Mean**	**3rd Qu.**	**Max.**
ΔSOC	t ha^{-1}	-1.1560	2.9487	3.658	3.7142	4.4397	11.0913

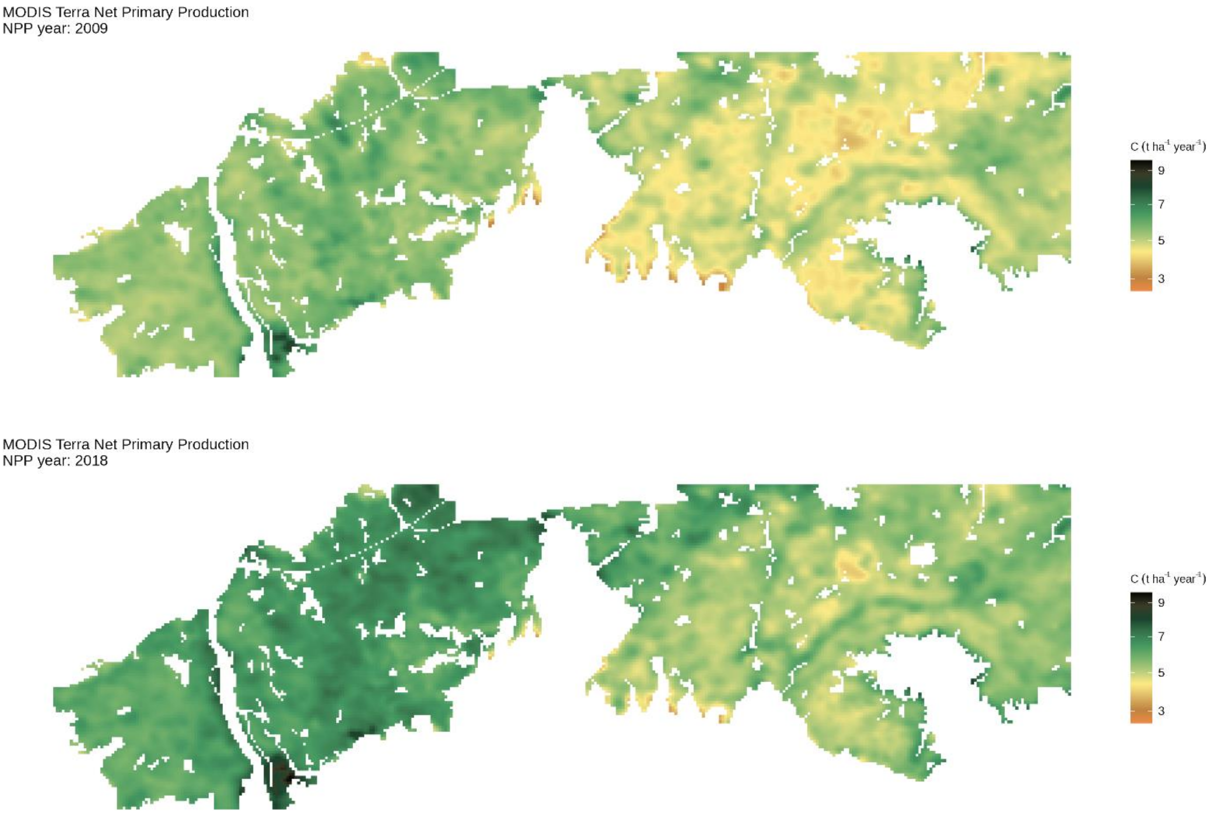

Figure 4.8. MODIS Terra NPP: 2009 (top), 2018 (bottom)

The temporal changes in SOC stocks are depicted in Figure 4.9, where the simulated distribution at the end of each year of the decade is displayed. The average annual SOC change during the decade was 0.343 t C ha^{-1} $year^{-1}$ with a range 0.11-0.6 and the smallest change occurring during 2011-2012, coinciding with the decade minimum of NPP distributions.

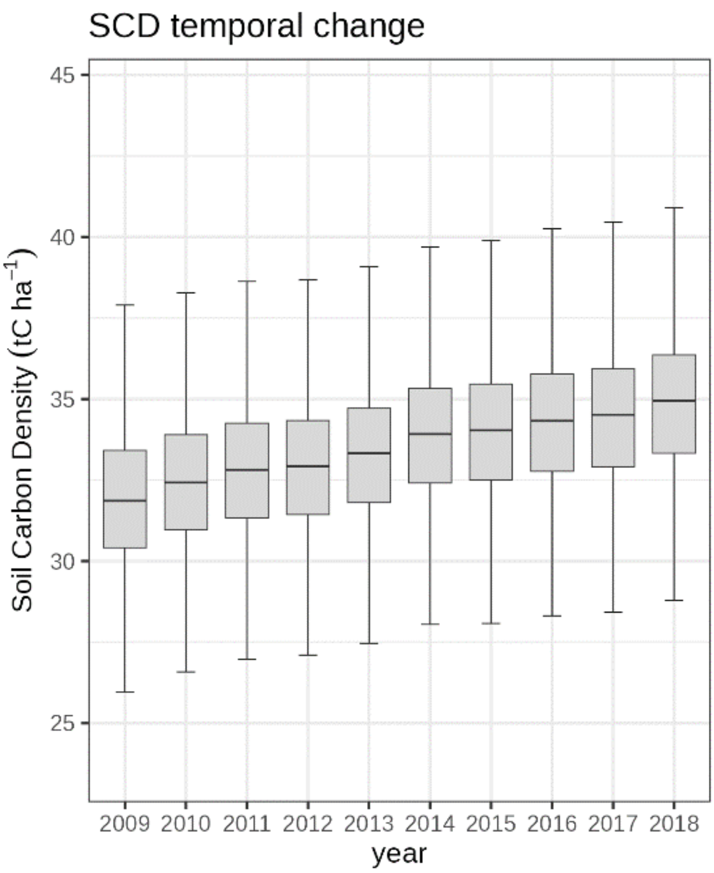

Figure 4.9. Soil Carbon stock temporal change

The quantified SOC stock changes were almost at an equal amount, positively correlated with Clay and negative correlated with initial carbon stock (SCD). The initial stock is one of the major controlling factors of SOC change. The results in Figure 4.10 suggest that soils with lower initial SOC concentrations might see larger SOC increase or lower soil C losses under otherwise comparable environmental and management conditions. Other researchers have similarly reported this inverse relationship between SOC change and initial SOC content (Wang et al., 2017; Tadiello et al., 2023).

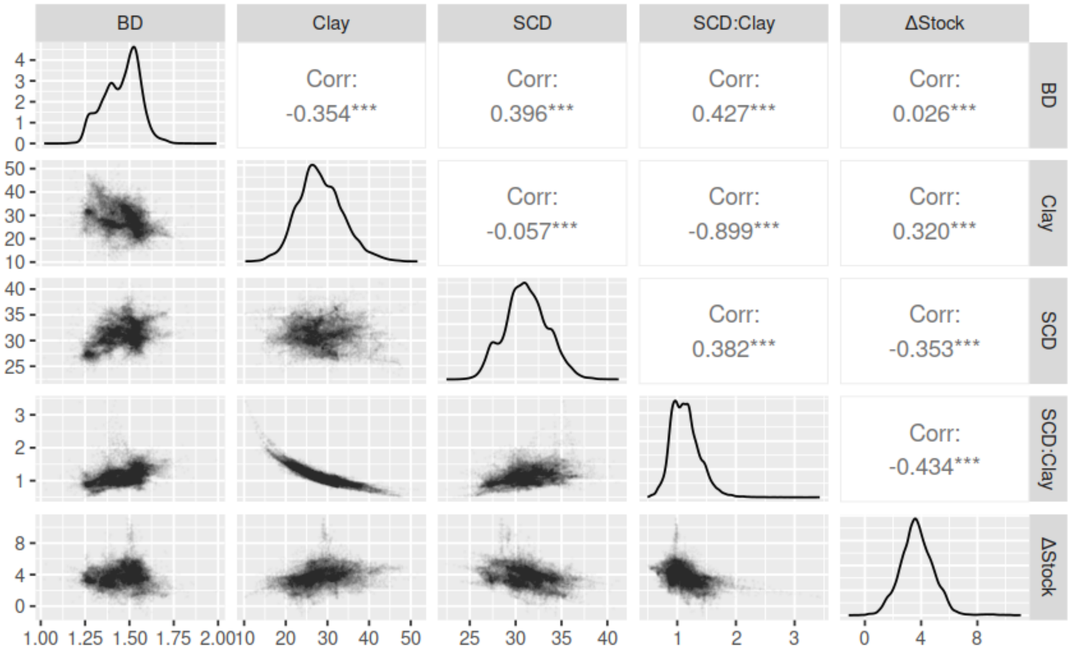

Figure 4.10. Correlation matrix for soil data & resulting ΔSOC

This negative relationship is further supported by the distribution of spatial patterns in the Initial SCD across the study area (Figure 4.11); soils with higher initial carbon stocks exhibit the lowest increase in ΔSOC (Figure 4.6).

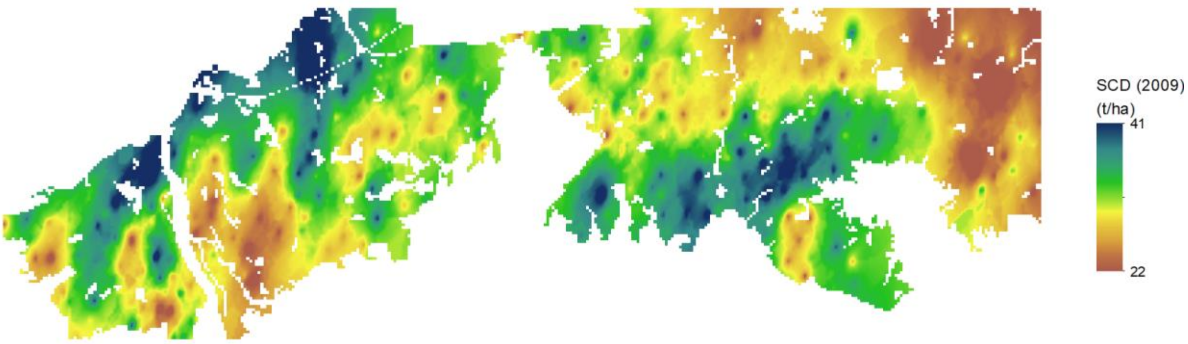

Figure 4.11. Initial carbon stock

Several authors have reported the positive effect of the clay percentage on SOC adsorption (Wang et al., 2017; Tadiello et al., 2023). This is related to the fact that clay soils exhibit strong aggregate formation and stability that prevents SOM decomposition. The optimum balance of soil organic carbon (SOC) and clay must be meticulously determined to achieve its beneficial effect on SOC sequestration. Tadiello et al., (2023) reported a maximum SOC/clay index threshold of 3.2 for positive effect on sequestration. Although in our case the SOC/clay index seems in the optimal region (Figure 4.13), if soils with higher initial SOC contents also have higher clay fractions, this would overshadow the beneficial contributions of soil clay to soil C accumulation. This result is supported by the distribution of SCD:Clay ratio in Figure 4.9, which is very close to 1.

4.3.2 STATISTICAL MODELS

A statistical modelling approach was adopted, similar to De Rosa et al., (2024), in order to assess the change in SOC stocks in the same study area of northern Greece during the period 2009-2018. The initial model formulation focused on 10-year changes in SOC concentrations (ΔSOC), assessed by fitting a quantile generalized additive model (qGAM) (Fasiolo et al., 2021) using the mgcViz R package (Fasiolo et al., 2020) on the revisited points of LUCAS topsoil (0–20 cm) surveys of 2009 and 2018. The trained model was then used for spatial predictions of ΔSOC. The response variable is the difference between SOC content from 2018 and 2009 revisited LUCAS points. To exclude land use change as a driving force of SOC changes, we focused only on the LUCAS points that remained in agricultural land use and land cover during 2009-2018. The distributions of interest from the selected LUCAS points are displayed in and Figure 4.12.

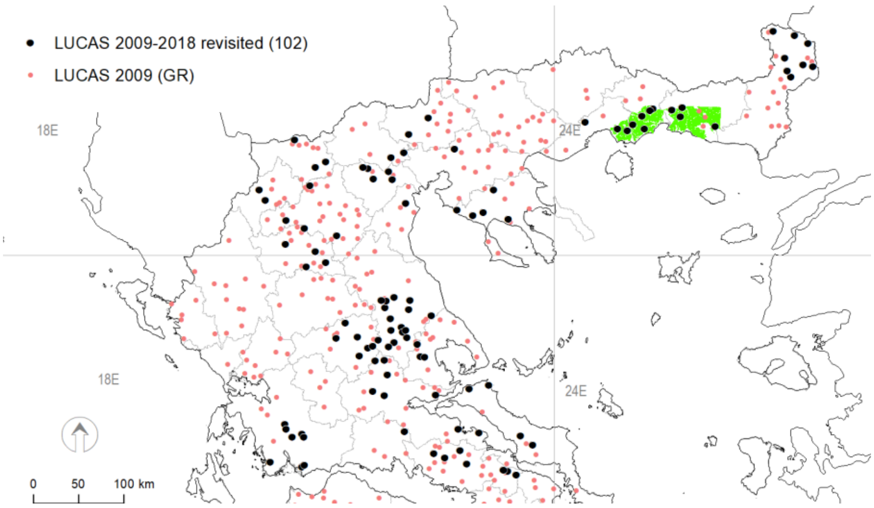

Figure 4.12. Revisited LUCAS points (2009-2018)

Table 4.5. LUCAS data statistics

AOI: input LUCAS statistics (n=102)									
variable	**units**	**Min.**	**1st Qu.**	**Median**	**Mean**	**3rd Qu.**	**Max.**	**sd**	**CV**
ΔSOC	g kg^{-1}	-11.2	-1.075	0.6	0.9265	3.075	12.6	4.116	444.3
SOC	g kg^{-1}	3.4	8.6	11.35	13.65	16.08	52.7	8.023	58.8
Clay Soil fraction	%	4	18	24	26.89	38	54	12.31	45.79

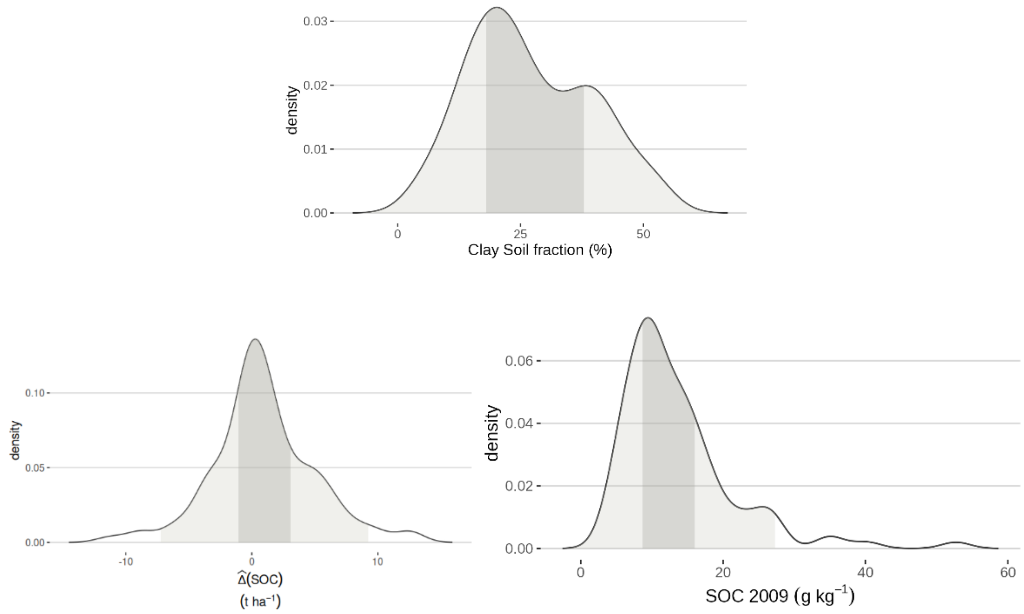

Figure 4.13. LUCAS data distributions

4.3.2.1 Predictors

The WorldClim Bioclimatic variables (Hijmans et al., 2005) concerning temperature and precipitation were used as predictors in the modelling process, along with the clay content and the initial SOC content (2009), log-transformed due to skewed distribution (Figure 4.13). To produce data that is more biologically significant, the bioclimatic variables are used to represent seasonality (e.g., the annual range in temperature and precipitation) and annual trends (e.g., the mean annual temperature).

The annual long-term mean precipitation (ann_P, mm) with precipitation seasonality (coefficient of variation, precCV), and the annual long-term temperature (mean annual temperature ann_T, °C) with temperature seasonality (standard deviation, tempSD), were extracted and included in the process (https://developers.google.com/earth-engine/datasets/catalog/WORLDCLIM). The final model included smooth effects from each of the two soil variables (log(SOC), Clay), and each of the four Bioclimatic variables, along with smooth nonlinear interactions of the soil variables, the temperature variables, and the precipitation variables, separately. Assessment of model performance was carried out using 10fold cross-validation. Visual inspection of partial dependence (PD) plots was employed to evaluate the contribution of each variable included in the model's predictions. PD plots depict the effect of a single predictor variable on the predicted outcome, with all other variables held constant. For spatial prediction the trained model was used to generate ΔSOC predictions across the study area using spatially explicit covariates at a resolution of 250 m. The initial SOC in 2009 and soil clay content were adopted from the RothC modelling approach, while the Bioclimatic variables were downscaled from native ≈ 1km to 250m (bilinear interpolation). The distributions of the Bioclimatic predictors are presented in Table 4.6.

Table 4.6. WorldClim data statistics

AOI: input WClim statistics (n=22550)									
BioClim variable	**unit**	**Min.**	**1st Qu.**	**Median**	**Mean**	**3rd Qu.**	**Max.**	**sd**	**CV**
Annual Precipitation	mm	728.1	784.9	830.3	822.1	855.8	949.9	43.54	5.296
Precipitation seasonality (CV)	%	54.01	65.26	68.29	67.62	70.61	73.1	3.629	5.367
Annual Temperature	℃	10.4	16.62	17.26	16.9	17.73	18.11	1.137	6.725
Temperature seasonality (SD)	℃	5.353	5.775	5.996	5.91	6.038	6.328	0.1848	3.127

4.3.2.2 Results

The revisited LUCAS points (Figure) showed ΔSOC to be extremely variable, ranging from -11 to 12 g C kg^{-1}, with a median of 0.6 g C kg^{-1} for the whole decade 2009-2018.

The qGAM prediction was fairly accurate as depicted in the console output with the modeling summary results:

```
summary(qfit)
Family: elf
Link function: identity
Formula:
DeltaSOC ~ s(log(SOC), k = 20) + s(Clay, k = 20) + s(ann_P) + s(precCV) +
       s(ann_T) + s(tempSD) + ti(log(SOC), Clay) +
       ti(ann_P, precCV) + ti(ann_T, tempSD)

Parametric coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)    2.646      1.274   2.077   0.0378 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Approximate significance of smooth terms:
                     edf Ref.df  Chi.sq  p-value
s(log(SOC))       16.129 17.194 195.286  < 2e-16 ***
s(Clay)           12.954 14.703 100.359  < 2e-16 ***
s(ann_P)           5.885  6.643  35.515 3.37e-06 ***
s(precCV)          8.370  8.640 128.671  < 2e-16 ***
s(ann_T)           3.070  3.618  24.861 4.73e-05 ***
s(tempSD)          5.313  6.150  49.923  < 2e-16 ***
ti(log(SOC),Clay) 11.707 12.476  74.716  < 2e-16 ***
ti(ann_P,precCV)   4.190  5.062  25.867 7.71e-05 ***
ti(ann_T,tempSD)   5.645  6.573   4.001    0.583
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
R-sq.(adj) =   0.722   Deviance explained = 90.5%
-REML = 328.91  Scale est. = 1          n = 102
```

The model explained 90% of the initial variability in the LUCAS data (ΔSOC). All the involved smoothing terms proved significant, with the exception of the smooth non-linear interaction between the temperature and its seasonality. The cross-validation error was also computed in t ha^{-1}:

```
# 10fold cross-validation
mean(cv.MSE$MSE) %>%
  sqrt()
[1] 1.12725
```

Each of the involved modelling terms (smoothing effects) is displayed in Figure 4.14. The investigation of PD plot (Figure bottom) revealed the interactions between the modeled variables. Lower initial SOC content combined with low clay levels had an overall positive influence on ΔSOC, while increasing initial SOC content had a negative effect on ΔSOC, regardless of clay content. Additionally, high annual mean precipitation at low-to-medium levels of inter-annual variability had a positive effect on ΔSOC. In contrast, warm and semi-arid climatic conditions (i.e. Mediterranean climate) promoted SOC losses.

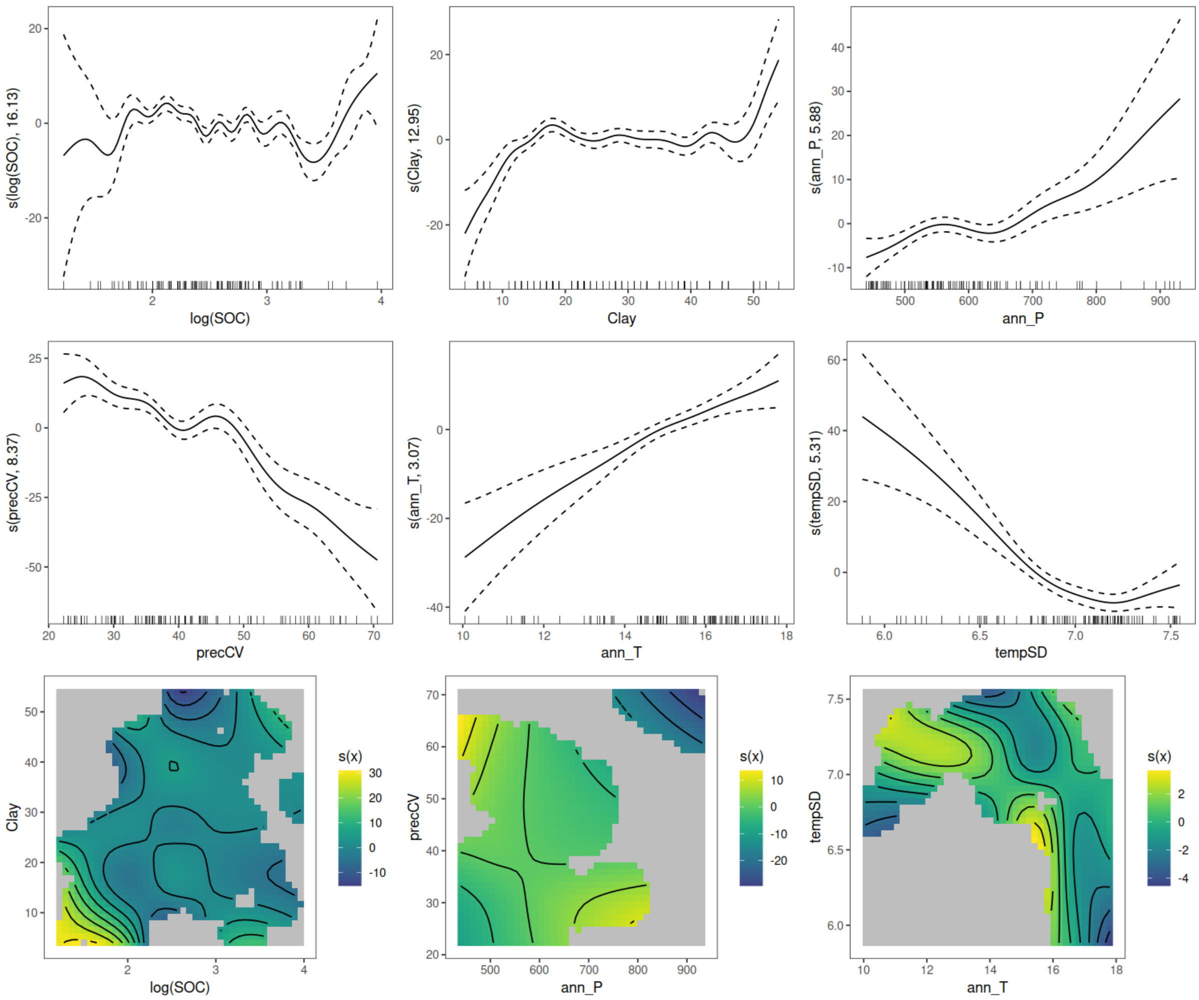

Figure 4.14. Main effect modelling terms (smooths) and non-linear interactions

4.3.2.3 Spatial prediction

Spatial prediction from the qGAM model was carried out in the study area, for the median quantile (q=0.5). The results are displayed in Figure 4.15.

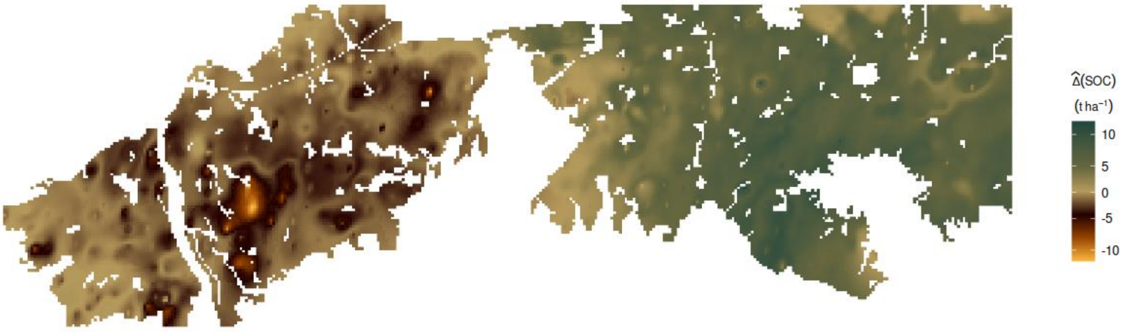

Figure 4.15. qGAM spatial prediction

Table 4.7. qGAM prediction statistics

AOI: qGAM statistics (n=22550)							
variable	**units**	**Min.**	**1st Qu.**	**Median**	**Mean**	**3rd Qu.**	**Max.**
ΔSOC	t ha^{-1}	-11.633	-1.607	1.772	1.980	5.802	11.920

The soil bulk density, which was employed to convert SOC concentration to stocks, was estimated using an empirically developed pedotransfer function, adopted from Hollis et al. (2012). The qGAM spatial prediction results reveal a general SOC increase in the study area during the decade 2009-2018, with a mean value of 1.98 t ha^{-1}. Statistics for the resulting distribution are presented in Table 4.7. The quantified SOC stock changes (Figure 4.15) also showed large spatial disparities across the study area, with the largest decrease appearing in a specific region in the western part of the area. These spatial patterns are controlled by the input LUCAS revisited dataset, whose input data on ΔSOC exhibits extreme variability ().

4.3.3 COMPARISON OF MODELLING APPROACHES

Although the two presented modelling approaches are fundamentally different, they are comparable since they both output soil carbon dynamics for the same time period and in the same units (t ha^{-1}). Judging by the statistically described distributions of both modelling results in Table 4.8, there is higher degree of agreement in the upper tails, i.e., the maximum values of C-dynamics, indicating that the resulting maximum level of predicted carbon stocks is realistic enough with respect to the input LUCAS point observations. The distribution across the study area is significantly different between the two modelling results, especially towards the lower end, where the qGAM model trained with LUCAS data, exhibits substantial stock losses locally in areas where the RothC model simulates steadily increasing carbon stocks. This result can be attributed to the inherent limitations of the RothC model; the possible leaching of organic matter is not considered, and the model lacks a management practices module, which is a feature of other models that can simulate the effects of fertilization, harvesting, irrigation, and erosion. Additionally, RothC does not consider additional water input types other than precipitation (i.e. water from irrigation). Water management during dry seasons can significantly impact SOC mineralization. The absence of these processes in the modeling framework is the current limitation of RothC and is the subject of several improvement efforts found in the literature (Farina et al., 2013; Hyun et al., 2024).

Table 4.8. Summarized modelling results

AOI: RothC – 2018 simulation and qGAM statistics (n=22550)							
model	**units**	**Min.**	**1st Qu.**	**Median**	**Mean**	**3rd Qu.**	**Max.**
ΔSOC RothC	t ha^{-1}	-1.1560	2.9487	3.658	3.7142	4.4397	11.0913
ΔSOC qGAM	t ha^{-1}	-11.633	-1.607	1.772	1.980	5.802	11.920

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5 CONSISTENT SOIL QUALITY RELATED DATABASES AND REFERENCES

Assessment of soil quality according to observations-based inventory requires the selection of the appropriate indicators from existing soil databases. In most cases, the number of soil quality indicators that are assessed on a particular set of soil samples needs to be limited to a minimum dataset. (Bünemann et al., 2018). Initially, the selection of minimum datasets was determined by expert judgment. Multivariate strategies for statistical data reduction like principal component analysis (PCA), became increasingly used later on. Given the limitations of finances, time, and various other constraints, choosing a minimal dataset derived from a wider range of soil quality indicators is an essential step in soil quality assessments to prevent collinearity. Currently, EU-scale soil quality related databases, with publicly available data from in situ observations, include the following major sources:

5.1 LUCAS soil observation data

The soil assessment component of the periodic LUCAS Land Use/Land Cover Area Frame Survey was initiated in 2009 from the EU Commission (Toth G, Jones A, Montanarella L. 2013). In 25 Member States (excluding Bulgaria, Malta, Romania, and Cyprus), composite soil samples were collected and analyzed based on the physical and chemical properties of the topsoil at a depth of 0-20 cm. The scope of the LUCAS Soil Component was to establish a harmonized dataset of the main topsoil properties in the EU. In total, approximately 22,000 soil samples were analyzed for cation exchange capacity, percentage of coarse fragments, pH, carbonates, organic carbon, total nitrogen, phosphorous, extractable potassium, particle-size distribution, spectral properties and heavy metals. During 2015, repetitive soil sampling was carried out in the initial point locations of LUCAS 2009/2012 to monitor the ongoing changes in physical and chemical topsoil parameters across the EU. Additionally, soil samples were collected in Bosnia-Herzegovina, Albania, Croatia, Montenegro, North-Macedonia, Serbia and Switzerland. Throughout 2016 and 2017, more than 27.000 soil samples were collected, analyzed and added to the collection. Within the LUCAS framework a new soil sampling campaign was carried out in 2018, with soil samples collected in repeated points of LUCAS 2009, 2012 and 2015 (Orgiazzi et al., 2018). Several new physical, chemical, and biological characteristics were investigated, including important indicators for assessing the quality of the soil, such as the bulk density and the biodiversity of the soil.

Due to the wide variety of soil properties considered, LUCAS Soil is one of the biggest and most complete, harmonized continental-scale soil databases in the world. Furthermore, it was designed as a scalable resource, allowing for the addition of new features and sample sites during subsequent sampling cycles.

Accessible to the scientific community and decision makers, data plays a crucial role in facilitating research and shaping the land-focused policy agenda. Moreover, the European Soil Data Centre (ESDAC) provides openly accessible data via this open-access service. (Panagos et al., 2012).

5.2 WoSIS soil profile data

The World Soil Information Service (WoSIS) provides standardized soil profile data to enable large-scale environmental applications and digital soil mapping. From the release of the first “WoSIS snapshot”, in July 2016, many new soil data were included, registered in the ISRIC data repository and subsequently standardized in compliance with the requirements of the data providers. Soil profile data managed in WoSIS were provided by numerous different data sources; consequently, particular focus was placed on measures for soil data quality and the standardization of soil property definitions, soil property values (and units of measurement) and soil analytical method descriptions. Several soil chemical and physical properties were taken into consideration. Additionally, for each soil profile the soil classification was also provided (FAO, WRB, USDA). Geographical data accuracy, along with the uncertainty of the analytical methods, are also available for further modelling assessments. The latest set of quality-assessed and standardized data is called “wosis_latest” and is accessible through OGC-compliant WFS services. The available snapshot (September 2019) includes 196498 geo-referenced profiles originating from 173 countries. They describe more than 832 000 soil horizons and 5.8 million records, under the framework of the Global Soil Information System (GloSIS) developed by the Global Soil Partnership (GSP). The current “WoSIS snapshot – September 2019” is available through public access at https://doi.org/10.17027/isric-wdcsoils.20190901 (Batjes et al., 2020).

5.3 National data

In Euro-MED area, many national approaches for the assessment of soil quality have been developed, relying entirely on the national-level soil mapping surveys that each country has carried out, collecting soil related information from in-situ observations. Each national repository has unique characteristics regarding sampling regime, analysis, metadata, soil depth profile, and there can be significant discrepancies between soil data across different databases, including methodology, purpose, and sampling strategies (spatial distribution & soil depth). A common bias in soil organic carbon measurements in many surveys is the overestimation of soil bulk density. Dry bulk density measurements are used for SOC density estimation from SOC concentration, but the main limitation of this approach at national scales is an over-estimation in bulk density measurements, due to up-scaling issues. Despite the lack of harmonization between national soil databases, they are recorded in Table 1 to assist future harmonization efforts similar to those from Uhran et al., 2021.

Table 5.1. National/Regional level Soil-quality related databases

	EU_MED Country/level	In-situ observations	Analytical data
1.	Greece / national and regional level	Augers, soil profiles	Basic physical/chemical in augers with BD and fragments vol. additional in soil profiles
2	North Macedonia / national and regional level	Augers, soil profiles	Basic physical/chemical parameters
3	Slovenia/national regional level (currently available)	Soil profiles	Basic physical and chemical properties of soil profiles (pH, texture, Soil organic carbon, SOM, total N, C/N, exchangeable phosphorus and potassium, exchangeable cations.)
4	Slovenia/national and regional level (in preparation larger soil database by KIS and also Ministry of Agriculture, Forestry and Food)	Soil profiles Soil layers	Basic physical and chemical properties of soil (pH, plant available phosphorus and potassium, total N, SOM, texture, cation exchange capacity, heavy metals, mineral oils, bulk density,...)

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6 IMPACT OF AGRICULTURAL PRACTICES, SOIL IMPROVING CROPPING SYSTEMS, AND CLIMATE CRISIS ON CROP PRODUCTION AND CARBON SEQUESTRATION

6.1 Introduction

The agricultural yields of primary crops (wheat, rice, maize, and soybean) have risen significantly during the past decades, driven by escalating global food and feed demands and facilitated by technological advancements. Agriculture is essential for global food security, but conventional agricultural practices, marked by intensive monoculture, significant dependence on synthetic inputs, and extensive soil tillage, have led to various environmental issues, including soil degradation, biodiversity loss, and heightened greenhouse gas emissions. In recent years, sustainable agriculture practices have emerged as a viable alternative to traditional methods, prioritizing measures that improve environmental quality, conserve natural resources, and provide economic sustainability for farmers (FAO 2020).

The significant potential of carbon sequestration in crops offers a feasible strategy for lowering atmospheric CO2 levels to mitigate climate change (Lal et al., 2016). This technique relies on cropping systems, which can be characterized as a framework for growers to follow in their crop production practices. An optimal farming system for carbon sequestration should generate and sustain a substantial quantity of biomass or organic carbon in the soil. Soil carbon sequestration is important for mitigating the effects of climate change and enhancing food security.

Climate change related issues like rising temperatures and increasingly frequent extreme weather events provide significant risks to crop yields and global food security. The rise in atmospheric CO_2 levels and anticipated climate change may affect global agriculture by altering plant growth and development, respiration, transpiration, and photosynthesis rates (Wang et al., 2010). Decreased soil fertility, deteriorating water quality, variations in groundwater levels, and increasing salinity in certain regions are now significant challenges for contemporary agriculture. A shortened growing season, water shortages, elevated temperatures, and heat stress during critical physiological stages of crops can lead to significant production reductions in arid and semi-arid regions globally (Rietra et al., 2022).

6.2 Impact of agricultural practices

The interactions between sustainable agricultural practices, crop yields, and soil carbon sequestration are complicated, with various factors affecting the results of these methods. Numerous studies (Blanco-Canqui et al., 2015; Pittelkow et al., 2015) indicate that the implementation of sustainable agricultural practices, including crop rotation, cover cropping, and conservation tillage, can enhance crop yields through enhanced soil fertility, superior pest management, and more effective water utilization. The use of sustainable agriculture practices may occasionally lead to trade-offs between crop production and soil carbon sequestration. No-till farming can enhance carbon sequestration by minimizing erosion and preserving soil structure; nevertheless, it may result in diminished crop yields in certain contexts due to the slower mineralization of organic matter and decreased nutrient availability. Recognizing and resolving these trade-offs is crucial for the effective implementation of sustainable agricultural practices (Saliu et al, 2023). Recent advancements in agricultural technologies, including precision agriculture and remote sensing, have created novel possibilities for optimizing sustainable farming practices and improving their impact on crop yields and soil quality. Schut et al. (2018) observed that the combination of precision agricultural technologies with sustainable practices, including site-specific fertilizer management and variable-rate irrigation, led to enhanced crop yields and reduced environmental impacts. Sustainable agriculture includes many farming strategies designed to improve the long-term production, resilience, and environmental sustainability of agro-ecosystems. The fundamental principles of sustainable agriculture are rooted in agro-ecology, highlighting the significance of conserving biodiversity, fostering nutrient cycling, and strengthening the resilience of agro-ecosystems against climate change and other environmental challenges. Common agricultural practices for sustainable agriculture include (Saliu et al, 2023):

Crop rotations

This practice enhances soil fertility by inhibiting the accumulation of pests and pathogens, regulating nutrient cycling, and preserving soil structure. Numerous research experiments appearing in meta-analysis publications in literature (Rietra et al., 2022) have shown that crop rotation can augment crop yields by improving soil nutrient availability, diminishing insect pressure, and facilitating more efficient water utilization. Crop rotations, when combined with conservation tillage, sequester greater amounts of soil carbon sequestration than mono-cropping, as demonstrated by numerous researchers conducting various field tests across diverse climatic conditions (Poeplau et al., 2015). Crop rotations, while having a lesser impact on soil carbon than other practices, can influence soil carbon through enhanced biomass production and carbon inputs from various crops, as well as by modifying pest cycles, diversifying root structures, and altering rooting depth. Crops that produce high residues may sequester more carbon than those with little residue input. The intensification of cropping systems, including an increased frequency of crops per year, double cropping, and the incorporation of cover crops, can enhance soil carbon storage (Mandal et al., 2020).

Cover cropping

The practice refers to the cultivation of non-harvested plants during or between the growth seasons of primary crops to provide multiple ecosystem services, including weed suppression, soil erosion mitigation, and nutrient cycling (Blanco-Canqui et al., 2015). Cover crops can improve soil health by increasing organic matter, enhancing soil structure, and fostering soil biodiversity. A meta-analysis by Wang et al. (2020) revealed that the use of cover crops significantly increased crop yields by an average of 14% and concurrently improved soil health metrics, including soil organic matter and nutrient availability. Cover crops can significantly increase soil organic matter by introducing fresh plant residues, promoting microbial breakdown, and improving soil carbon sequestration. The meta-analysis conducted by Poeplau and Don (2015) indicated that cover cropping significantly enhanced soil organic carbon stocks, with the most substantial gains occurring when cover crops were cultivated in mixtures rather than as monocultures.

Conservation tillage

This practice comprises a series of soil management techniques designed to minimize soil disturbance and preserve soil cover, hence reducing soil erosion, sustaining soil structure, and improving water infiltration. Conservation tillage strategies encompass no-till, reduced tillage, and strip tillage (Kassam et al., 2019). Research indicates that conservation tillage enhances soil health by augmenting soil organic matter, fostering soil biodiversity, and diminishing soil compaction (Blanco-Canqui et al., 2015). The effect of conservation tillage on crop yields is context-dependent, with certain studies indicating yield increases and others indicating reductions (Blanco-Canqui et al., 2015; Pittelkow et al., 2015). The advantages of conservation tillage in reducing runoff and soil erosion are well recognized and when utilized alongside crop residues and cover crops, conservation tillage enhances soil structure and increases the soil organic carbon pool. The advantages of conservation tillage in carbon sequestration arise from both the enhancement of soil organic carbon (SOC) content and the reduction of CO_2 emissions associated with plowing, as well as decreased fuel consumption. Reportedly, the effect of conservation tillage on soil organic carbon sequestration may be more pronounced in degraded soils compared to fertile soils (Mandal et al., 2020).

Organic farming

Organic farming practices are an agricultural approach that utilizes natural processes and inputs, including compost, manure, and biological pest control, to improve soil fertility and manage pests, as opposed to synthetic fertilizers and pesticides (Mandal et al., 2020). Organic farming generally produces lower crop yields compared to conventional farming because of the diminished utilization of synthetic inputs. Nevertheless, certain studies indicate that organic systems can attain yields comparable to conventional methods under specific circumstances, especially when integrated with other sustainable agricultural practices or cultivated in soils rich in organic matter. A meta-analysis study (Seufert et al., 2012) revealed that organic yields were, on average, 19-25% inferior to conventional yields; however, the yield gap dropped to 9% under ideal conditions. Organic farming can improve soil organic matter by integrating organic materials, such as compost and animal dung, into the soil and fostering soil microbial activity. Gattinger et al. (2012) conducted a meta-analysis study revealing that organic farming enhanced soil organic carbon stocks by an average of 18% relative to conventional farming, with the most significant increases noted in systems characterized by high organic input rates.

Agroforestry

Agroforestry is a land-use strategy that combines trees with crops and/or livestock to develop multifunctional landscapes. These practices can improve soil health by increasing soil organic matter, enhancing nutrient cycling, and fostering soil biodiversity (Mandal et al., 2020). Agroforestry systems offer several ecological services, including carbon sequestration, microclimate regulation, and habitat supply for pollinators and other beneficial species. Numerous studies have shown that agroforestry can augment agricultural yields by raising nutrient availability, improving water use efficiency, and offering shade and wind protection (Smith et al., 2012; Coe et al., 2014).

6.3 Impact of Soil Improving Cropping Systems

The concept of 'cropping systems' represents the crop variety, crop rotation, and agronomic management practices employed in a specific field over several years. Decisions on these factors can affect both the viability and sustainability of agricultural production. These systems are defined as soil-improving if they lead to a sustained enhancement of the soil's capacity to perform its functions, particularly food and biomass production, buffering and filtering capacities, and the maintenance of additional ecosystem services (Hessel et al., 2022). Soil Improving Cropping Systems (SICS) can adopt and combine several management approaches like crop rotation, inter-cropping, and cover crops between growing seasons, crop-residue management, manure application, reduced tillage or no-tillage, N-fertilization with straw/stalk and more. A thorough literature review revealed the reported results from several meta-analysis studies on SICS evaluation, mainly with the use of data from long-term experiments (LTEs) across EU and worldwide, emphasizing the advantages as well as the challenges of SICS adoption in the long-term i.e. decade-long application or more.

The results from LTEs and meta-analysis studies (Rietra et al., 2022; Poeplau et al., 2015) indicated a slight beneficial effect of SICS on the environment, including soil quality, no influence on sustainability, and a minor negative impact on economics and the sociocultural dimension. Certain treatments exhibited both elevated and diminished impact scores across the parameters of the sustainability assessment, highlighting the trade-offs in the effectiveness of a SICS. Certain treatments resulted in either negligible or adverse effects (e.g., early wheat sowing), while other treatments had favorable impact ratings across all dimensions (e.g., nitrogen fertilization with straw/stalk). SICS possess the capacity to lower long-term expenses by minimizing dependence on costly external inputs like fertilizers and pesticides, decreasing energy consumption for machinery operation, and/or limiting labor requirements. Even though certain SICS can result in lower productivity i.e. crop yield, they might use inputs more efficiently because of their increased efficiency (Hessel et al., 2022).

The significant potential of carbon sequestration in agricultural land offers a feasible strategy for reducing atmospheric CO2 levels to mitigate climate change. This technique relies on SICS as operational frameworks for growers to adhere to in their crop production practices. An optimal farming system for carbon sequestration should generate and sustain a substantial quantity of biomass or organic carbon in the soil. The concentration of organic carbon in the surface soil (0-15 cm) mostly relies on the total input of crop residues either left on the surface or integrated into the soil. Removing crop residues from the soil significantly reduces soil carbon levels. Consequently, enhancing carbon sequestration necessitates an increase of plant biomass residue input (Wang et al., 2010). Biomass accumulation can be increased through higher cultivation intensity, the cultivation of cover crops during inter-cropping seasons, the reduction of land fallow periods, crop rotations, and inter-cropping systems. The return of biomass to the soil can be enhanced by eliminating summer or winter fallow and maintaining a dense vegetative cover on the soil surface, which also mitigates soil erosion and prevents soil organic carbon loss. Insights concerning results from individual or combined SICS applications through LTEs are summarized below.

Crop rotation

The impacts of crop rotation, inter-cropping, and cover crops on crop productivity, soil quality, and the environment were generally favorable in nearly all studies (Rietra et al., 2022). The results are dependent upon the nitrogen fertilization rate: yield benefits are maximized during low nitrogen fertilization. The parallel cultivation of multiple crop species inside a single field for certain parts of the growing season (inter-cropping) positively influences crop output; however, the magnitude of this effect is highly dependent upon the specific crop varieties and inter-cropping configurations employed. Implementing cover or catch crops following the primary crop mitigates soil erosion and nitrate leaching while enhancing soil carbon sequestration.

Further results indicate that poor crop rotation will eventually lead to a decline in soil productivity and biomass production, resulting from an increase in infestations from weeds, diseases, and insects (Wang et al., 2010). Enhancing cropping intensity by minimizing the duration of bare land fallow during crop rotation is an efficient strategy to augment biomass output and soil carbon sequestration. Furthermore, higher cropping intensity can reduce the rate of organic matter decomposition and the mineralization-oxidation of SOC. Similarly, cover cropping systems offer an effective approach to enhance carbon sequestration for climate change mitigation (Baartman et al., 2022). Meta-analysis studies (Rietra et al., 2022; Poeplau et al., 2015) highlight the fact that soil organic carbon sequestration rates seen in most global cover crop studies are comparable to those associated with other organic-input-related carbon sequestration management strategies in agricultural soils and are nearly as effective as land-use changes such as the afforestation of croplands. Carbon sequestration could continue for many decades, but approximately 50% of the overall impact on soil organic carbon stores is anticipated to take place over the initial twenty years. This strong sequestration rate, along with the extensive geographical availability of possible cultivation sites, supports the belief that cover crop cultivation is a sustainable and effective strategy for mitigating climate change. Furthermore, cover crops can mitigate nutrient leaching and improve nutrient efficiency, decrease wind and water erosion, and assist with pest management, rendering cover crops environmentally beneficial and economically sustainable in the long term.

Tillage

Tillage directly affects soil carbon content. Tillage may have both beneficial and harmful effects on the soil C pool. The negative impacts of tillage include erosion, leaching, and mineralization, whilst the beneficial effects involve the humification of plant residues, mineral aggregation, organic compound synthesis, and the deep deposition of carbon in soil horizons. Conservation tillage is a broad concept that seeks to preserve moisture and minimize runoff losses. Conservation tillage may include no-tillage, reduced tillage, ridge tillage, and mulch tillage. All these tillage approaches adhere to three fundamental principles: i) minimal soil disturbance, ii) retention of crop residues on the soil surface, and iii) no or minimal traffic on the agricultural land (Busari et al. 2015).

Meta-analysis studies have shown that conservation tillage, including no-tillage or reduced tillage, often leads to decreased crop yields, increased soil organic carbon (SOC) contents in the topsoil, higher soil biodiversity and increased abundance of soil organisms, compared to conventional tillage. However, it also results in greater emissions of nitrous oxide (N_2O), and the extent of these effects vary with climate conditions (Hessel et al., 2022). The yield penalties associated with no-tillage are closely related to crop residue return and crop rotation and tend to be more significant in tropical regions compared to temperate regions. Notably, these penalties diminish with the prolonged use of no-tillage practices. Although no-tillage typically incurs lower production costs than conventional tillage, the additional carbon sequestration it provides is minor and highly variable, leading to fluctuations in the net economic benefits (Hessel et al., 2022).. Long-term experiments (LTEs) have demonstrated that combining conservation tillage with crop residue significantly enhances carbon sequestration compared to conservation tillage alone. To maximize soil carbon sequestration, larger quantities of plant residues must be returned to the soil while keeping soil disturbance to a minimal (Wang et al., 2010).

Crop residue

In conservation agriculture, crop residues are returned to the soil to improve soil quality and reduce soil erosion, often in conjunction with zero-tillage or reduced-tillage practices. LTEs have shown that crop residue management and mulching lead to increased crop yields, with improvements in water and nitrogen usage efficiency. By reducing soil evaporation, mulching allows more water to be available for crops, leading to higher yields (Rietra et al., 2022).

Results from LTEs across the European Union (EU), have demonstrated that incorporating agricultural residues into the soil or applying farmyard manure significantly improves soil structure, including water-stable aggregates and bulk density. However, soil organic carbon content and plant-available water content did not show substantial increases despite these beneficial effects on yield and soil structure (Hessel et al., 2022). Other LTEs (Poeplau et al., 2015) found that manure application mitigated the yield gap between organic farming and conventional treatments using mineral fertilizers, while also decreasing soil bulk density. Studies examining sustainable intensification cropping systems (SICS) with varied crop residue management showed that returning crop residues reduced the need of fertilizers. Overall, crop residue return has a positive impact on soil carbon sequestration and soil microbial activity, although it is associated with increased N_2O emissions (Rietra et al., 2022). Conservation agriculture, which integrates crop residue mulching and no-till, can increase soil organic carbon by conserving water, minimizing soil erosion, improving soil structure, and lowering atmospheric CO_2 enrichment levels (Rietra et al., 2022). Ridge tillage, when combined with fertilizers and crop residues, have also proven effective in sequestering soil organic carbon particularly through erosion control (Baartman et al. 2022).

6.4 Impact of climate crisis

The climate crisis, coupled with extreme weather events, poses significant risks to global crop yields and their stability globally (Reyes et al., 2021). The four primary climatic factors influencing crop productivity are rising atmospheric temperatures in the atmosphere, changes in precipitation patterns, increased CO_2 concentration, and rising tropospheric ozone (O_3) levels (Lobell and Gourdji 2012).

Global temperatures are increasing at a rate of approximately 0.3 °C for maximum temperatures and 0.2 °C for minimum temperatures per decade. Higher temperatures are likely due to an increased occurrence of heat events and a reduced frequency of cold events, both of which affect crop growth and quality. Projections indicate that global temperatures will rise by 1 °C within the next decade, with agricultural regions experiencing an even greater increase due to faster warming of terrestrial areas compared to oceans (Tariq et al., 2020).

Temperature directly impacts crop development and yield through its effects on photosynthesis, water use, crop duration, and susceptibility to physical damage and pest infestations (Lobell and Gourdji 2012). Precipitation variability also significantly influences crop yield by affecting soil moisture, which is crucial for crop growth. Southern Europe (Tariq et al., 2020) is expected to experience more severe droughts, leading to higher water stress for crops. Drought conditions promt plants to close their stomata, which limits carbon uptake and exacerbates heat stress, further reducing crop growth and yield. Conversely, increased precipitation can lead to flooding and waterlogging, which damage crops and reduce soil fertility (Hatfield et al. 2011). Temperature dynamics under climatic change involve more extreme heat events, which are harmful to crops, and fewer cold waves (Tariq et al., 2020).. Crops vulnerable to high temperatures will become increasingly susceptible to heat waves, resulting in earlier senescence, shorter grain-filling periods, impaired leaf water relations, and photosynthetic suppression (Asseng et al. 2015).

Since the industrial revolution, atmospheric CO_2 concentrations have risen by 46.5% from 278 ppm to 407.4 ppm in 2018, with an average annual increase of 2 ppm in the 2000s (Lobell and Gourdji 2012). CO_2 levels are projected to reach 500 ppm by the mid-21st century (IPCC 2001). The global increase in CO_2 levels mitigates some of the negative effects of rising temperatures and intensifying droughts, enhancing global crop yields by approximately 1.8% per decade. However, temperature increases are expected to reduce crop yields by around 1.5% per decade (Tariq et al., 2020). The interaction between higher CO_2 levels and rising temperatures present both opportunities and challenges for crop productivity, with CO_2 boosting photosynthesis and growth, but potentially failing to offset yield losses caused by heat stresses (Chavan et al., 2019).

Air pollution from sources like nitrogen oxides, carbon monoxide, and methane has led to rising tropospheric ozone (O_3) levels, which increased from 10–15 ppm in the preindustrial era to over 35 ppm due to elevated industrial emissions. Future O_3 levels remain uncertain due to gaps in understating O_3 emission mechanisms and pollutant control strategies (Tariq et al., 2020). Effects of climatic change on crop production are complex, with interactions between temperature, CO2, and O3 making it difficult to predict the net impact of these variables (Sangeetha et al. 2018).

Soil carbon sequestration offers a potential strategy for mitigating the adverse impacts of climate change on food security (Lal 2016). Climate-induced changes in temperature and precipitation affect the decomposition rates of SOC and the balance between storage and release. Soil organic carbon stock commonly increases as global temperatures decline. Cold and humid regions exhibit elevated soil carbon content in contrast to semiarid and arid climates. The climate and the type of organic matter added to the soil are significant factors affecting CO_2 output. Elevated temperatures result in increased CO_2 output from the soil. As global temperatures rise, decomposition accelerates, reducing the retention time of carbon in the soil (Hammad et al. 2020). This suggests that soils could become a significant source of CO_2 emissions in the future. Soil organic matter originates from the decomposition of plant and animal wastes and the ongoing degradation of these plant components yields more stable forms known as humus. Typically, humus can persist in the soil for approximately 27 years. It is now widely recognized that the decomposition of soil organic matter is an ecosystem characteristic rather than simply a compositional attribute (Schmidt et al. 2015). The decomposition of organic molecules in an ecosystem is conditional to environmental and biological factors. The decomposition process impacts soil biodiversity. An accelerated breakdown process in soil promotes the accumulation of microbial communities. Factors like moisture, temperature, material decomposition, and microbial community structure influence the residence period of the introduced carbon source in the soil. Consequently, understanding these dynamics is crucial for effective soil carbon management (Schmidt et al. 2015).

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7 CONCLUSIONS

Soil quality monitoring in Euro-MED region is essential to effectively manage agricultural systems and improve productivity without causing environmental degradation. This deliverable focuses on the monitoring of Soil Organic Matter (SOM) and soil quality. It sets forth defined goals regarding the main aspects of soil quality assessment. The key points regarding the objectives set in Chapter 1, are discussed below and have been achieved by a thorough and detailed examination and reporting of the most important scientific advancements specifically related to SOM.

- **Selection of indicators to assess soil functioning, standardization of reference values of soil indicators, and selection of a Minimum Data Set.** The assessment and measurement of soil quality are typically determined by considering the spatial and temporal variations of specific properties. Several basic soil characteristics has been suggested as indicators of soil quality. From this collection of data, it is possible to derive other significant indications such as water availability, microbiological quotient, and respiratory quotient. A suggested standard for soil quality indicators is the capacity to identify a 10% change with a 90% confidence level. Certain indicators may suffer due to their significant temporal and/or geographical variation, or difficulty in interpreting their reaction to change. Choosing a suitable set of indicators or using substitute indications for a soil quality assessment is a crucial first stage in monitoring soil quality.
- **Propose carbon sequestration models adapted for MED agriculture**. Both probabilistic or process-based models, and stochastic or statistical models were examined and tested in typical Med conditions. A thorough literature review revealed the advantages and shortcomings of several modeling efforts, facilitating the modeling choices for future development. SOM models are utilized extensively as valuable tools for bringing together and examining experimental data, describing effects, and extrapolating results. Additionally, they are employed to project the behavior of SOM under present and future environmental conditions. Furthermore, these models aid in decision-making processes across multiple levels and by diverse users. SOM models continue to be among the most significant tools we have for enhancing our understanding of the dynamics of soil organic matter.
- **Propose standardization of soil sampling schemes and building consistent soil quality related databases.** Compliance with existing databases like LUCAS and WoSIS is essential; given the extensive range of soil characteristics considered, LUCAS Soil is one of the largest and most comprehensive, standardized soil databases on a continental scale worldwide.

- **Propose analytical determination of organic carbon in soil and simple on-field procedures** (in-situ check of soil quality). Recent advancements in quick dichromate oximetric colorimetric techniques, which entail subjecting the sample to refluxing with external heating, provide SOC (soil organic carbon) values that are equivalent to those produced using automated dry combustion procedures. A straightforward and efficient method for measuring the easily decomposable carbon in soil by mild permanganate oxidation has the potential to identify changes in soil organic matter quality at an early stage. Each technique for determining SOC has inherent limitations, and the user should choose the approach that is most suitable for the kind of soils being studied, the anticipated recovery, and the desired level of accuracy for the findings.
- **Propose SOM monitoring methodology;** possible inclusion of novel Near-Infrared Reflectance Spectroscopy or colorimetry-based techniques. With recent improvements in VisNIR equipment, it is now feasible to get in situ VisNIR spectra measurements from soils.
- **Evaluate the impact of agricultural practices, Soil Improving Cropping Systems, and climate crisis on crop production and carbon sequestration**. Numerous findings exist about carbon sequestration or soil organic carbon storage in croplands via integrated cropping systems and techniques, including conservation tillage, cover cropping, crop rotation, shifting cultivation, and fertilization. The soil organic carbon pool possesses significant potential for carbon sequestration, and integrated cropping systems, together with associated agricultural practices, have demonstrated good prospects for atmospheric carbon capture and climate change mitigation. In conclusion, sustainable farming practices can improve crop yields and soil health, while simultaneously fostering the conservation of natural resources and reducing environmental consequences. The literature review indicates that sustainable agricultural practices, including crop rotation, cover cropping, conservation tillage, and organic farming, enhance soil organic matter, nutrient cycling, and soil biodiversity, thereby increasing crop yields and carbon sequestration potential.