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Carbon Farming: How to Support Farmers in Choosing the Best Management Strategies for Low-Impact Food Production

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Abstract: The European Commission is directing efforts into triggering the storage of carbon in agricultural soils by encouraging the adoption of carbon farming practices under the European Green Deal and in other key EU policies. However, farmers that want to enter this production model urgently need to define the sustainable practices required for increasing soil organic carbon without overturning production systems and also need to adapt it for optimizing yields and improving carbon stocks. However, there is still a lack of tools that are easy to use and interpret for guiding farmers and stakeholders to find ways in which to increase soil organic carbon content. Therefore, this research aims to set up a novel bottom–up approach, in terms of the methodology and analysis process, for identifying tailored sustainable farming management strategies for the purpose of increasing soil carbon. We investigated 115 real food production cases that were carried out under homogeneous pedo-climatic conditions over a period of 20 years in the Apulia region (Southern Italy), which made it possible to create a dataset of 12 variables that were analyzed through a decision tree (created with the C4.5 algorithm). The overall results highlight that the treatment duration was the most crucial factor and affected the carbon stock both positively and negatively. This was followed by the use of cover crops alone and then those in combination with a type of irrigation system; hence, specific agricultural management strategies were successfully identified for obtaining effective carbon storage in the considered real food production cases. From a wider perspective, this research can serve as guidance to help EU private actors and public authorities to start carbon farming initiatives, pilot projects, or certification schemes at the local and/or regional levels.

Keywords: sustainable food systems; agricultural management strategies; climate-positive practices; soil carbon stock; European policy; decision tree

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1. Introduction

In 2021, the European Commission set out to shift to a climate-neutral economy by 2050. In the same year, the European Climate Law turned this target into a legal commitment, specifically to a greenhouse gas (GHG) emission reduction of at least 55% by 2030 [1]. The agricultural sector is responsible for 10% of the total European Union (EU) GHG emissions; as such, the EU's commitment is crucial for increasing carbon sequestration and for achieving reductions in these emissions [2]. In addition to the mandatory contribution of this sector, it is important to underline that agriculture can play a key role in the achievement of EU targets thanks to agricultural soil's function as a carbon sink [3]. Recently, the European Commission has been directing efforts into the storage of carbon in agricultural soils and encouraging farmers to adopt practices that comply with this aim. The Commission defines carbon farming as follows: "A green business model that rewards land managers for taking up improved land management practices, resulting in the increase of carbon sequestration in living biomass, dead organic matter and soils by enhancing carbon capture and/or reducing the release of carbon to the atmosphere, in respect of ecological principles favorable to biodiversity and the natural capital overall" [4]. In brief, carbon farming consists of the management of carbon pools, flows, and GHG emissions with the purpose of mitigating climate change. The increase in carbon storage will, in turn, feed into the EU Emissions Trading System, which is an important instrument for cost-effectively reducing GHG emissions [5].

In March 2020, the Commission adopted the new Circular Economy Action Plan (CEAP), which is one of the main building blocks of the European Green Deal [6]. This plan highlights that carbon removal can be nature-based by putting into place several strategies, including carbon farming. Additionally, as announced in the CEAP, the Commission intends to incentivize the uptake of carbon and increase its circularity by developing a regulatory framework for the certification of carbon storage based on robust and transparent carbon accounting. Furthermore, as stated in the EU Farm to Fork Strategy, the Commission adopted the Communication on Sustainable Carbon Cycles in December 2021 to motivate the agricultural sector to tackle climate change [4,7]. The Communication defines actions to upscale carbon farming with the aim of rewarding farmers who implement practices for carbon sequestration. These actions are as follows: (i) the promotion of carbon farming practices in the frame of the EU Common Agricultural Policy (CAP) and other funding programs (e.g., LIFE and Horizon Europe), particularly within the Mission "A Soil Deal for Europe" and national funding programs; (ii) the implementation of standard and reliable methodologies for accounting and monitoring carbon farming; and (iii) the advancement of farmers' knowledge about data collection and processing and the provision of ad hoc consultancy services [4]. Also, the Commission carried out a two-year study from 2018 to 2020 on setting up and implementing carbon farming in the EU [3]. Based on the results of the study, as well as those of thematic projects and events, the European Commission launched their carbon farming initiative at the end of 2021. This study stated that carbon farming practices can contribute to the EU's efforts in tackling climate change through the sequestration and storage of carbon. Also, carbon farming has been recognized as an innovative green business model that generates a novel form of income for bioeconomy actors, thereby taking into account the climate benefits they provide [3,8]. Furthermore, carbon farming has been promoted by the new EU Common Agricultural Policy 2023–2027 (CAP), which informs about and rewards good agronomic practices. Within the approved CAP 28 Strategic Plans, carbon farming is included among the eco-schemes targeted at soil conservation [9], while certain agricultural practices (e.g., the use of leguminous crops, crop diversification, tillage restrictions, and green cover in permanent crops) are recommended to increase soil carbon sequestration ability [10].

Increasing soil organic carbon (SOC) and endorsing carbon farming produce multiple benefits for farmers that span from improvements in soil quality to increases in productivity [11]. This is particularly true in certain territories where the agricultural sector is threatened by several issues, such as natural resource erosion and impoverishment [12], extreme weather events [13], and increased production costs [14]. According to the Thematic Group on Carbon Farming, knowledge and understanding of effective agricultural practices for SOC are of paramount importance in order to increase farmers' interest and involvement in this initiative [15]. Many efforts have been made by the scientific community to find fast and easy ways to determine SOC content while producing low amounts of dangerous wastes or to predict CO_2 fluxes [16–19], but recent research has focused more on predicting the effects of certain agricultural practices on SOC [20–23] rather than on supporting farmers in choosing the most suitable management strategies for carbon stock improvement. Currently, the United Nations is pushing to contrast climate change by suggesting an increase in SOC [24], and the FAO is providing a tool for illustrating how much CO_2 is sequestrable in soils and for informing on good practices to maintain SOC stocks [25]. In this view, the scientific community has focused attention on SOC increase or maintenance, but in many pieces of research, data mining or machine learning approaches have been adopted for mapping current SOC levels [26–28], predicting SOC ecological dynamics [29–31], or tuning analytical methods for quantitative SOC determination [32–34]. Consequently, there is still a lack of tools that are easy to use and interpret for guiding farmers and stakeholders in finding and suggesting ways to increase SOC content. The above aims, targets, and approaches relapse on farmers and stakeholders; as such, a bottom–up standpoint should be considered for supporting these final actors in making the proper choices.

Considering this complex scenario, this paper aims to provide a concrete decision support tool tested on real farming experiences that can offer to farmers multiple choices (besides economic feasibility or agricultural productivity alone) related to adoptable agricultural practices or management strategies that increase SOC storage. In turn, this can allow farmers to not have to overturn the existing production system but rather adapt it for optimizing yield and increasing SOC. More than 100 real food production cases were carried out over a period of 20 years in the same pedo-climatic conditions, and these were used for the purpose of creating a dataset that includes several agricultural practices and three classes of SOC variation. Then, this dataset was processed through a decision tree (i.e., the C4.5 algorithm) [35].

This paper is organized as follows: After describing the materials and methods in Section 2, the results and their discussion are reported in Section 3. Finally, Section 4 presents the conclusive remarks.

2. Materials and Methods

2.1. Data Collection

The data used in this research were collected from the library of CIHEAM Bari (Valenzano, Apulia Region, Southern Italy) by consulting 50 documents that are publicly available, including master's and PhD theses, scientific papers, and project reports, whose related activities were carried out in the experimental field of CIHEAM Bari (41°03′16″ N 16°52′33″ E, Figure 1) from 2001 to 2021.

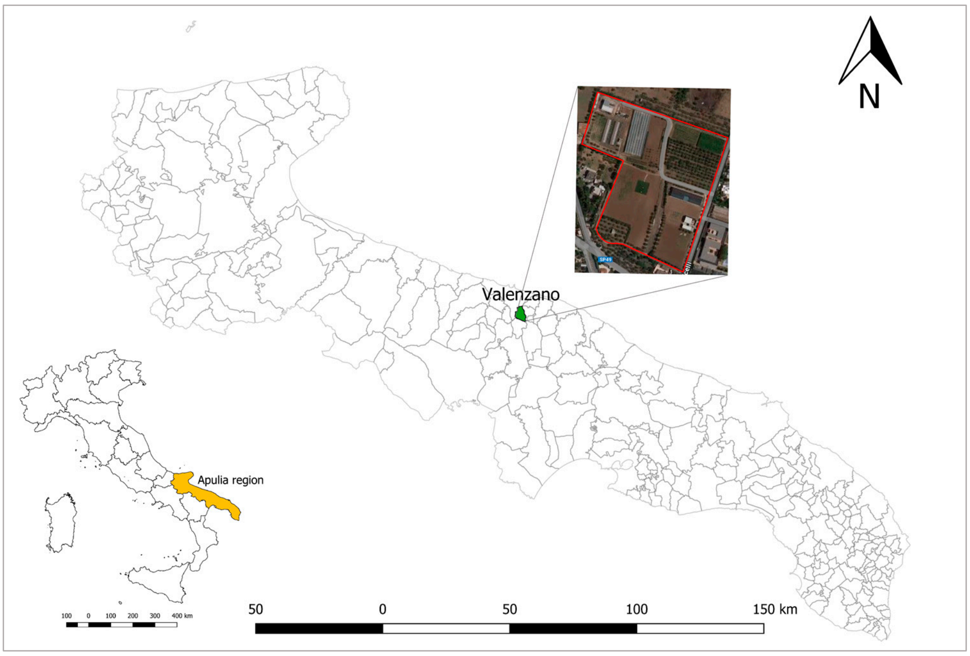

Figure 1. The location of the experimental field at CIHEAM Bari (41°03′16″ N 16°52′33″ E).

This field was chosen because of the homogeneity of its soil physical parameters and certain chemical characteristics. It extends for about 4.5 ha; it is almost plain and moderately stony; and the soil is clay–loam according to the USDA classification [36], characterized by sub-alkaline pH (between 7.5 and 8), low nitrogen content (<1.5 g·kg^{-1}), and poor levels of organic matter (<20 g·kg^{-1}). The climate is typically Mediterranean with hot dry summers and humid, cool winters with rapid heavy rains or strong winds from the southeast and northwest [37]. The specific climate data from 2001 to 2021 are as follows: an average winter temperature of 8 °C, an average summer temperature of 25 °C, and an average rainfall equal to 600 mm.

Out of the 50 documents consulted, 21 of them were selected because they reported a variation in the SOC across 115 real food production cases (RFPCs) that were carried out in the experimental field. In addition, these 21 documents were suitable for constructing a dataset of variables that describe the common practices affecting the SOC content in the 115 RFPCs. The final dataset consisted of 12 categorical variables, including at least two and at most seven possible categorical values, which were selected considering their relevance in soil organic carbon dynamics [38]. Below is a list of the 12 variables that made up the dataset:

- Site (S). This includes the RFPCs that were carried out in open fields or under tunnels;
- Treatment duration (TD). This classifies the crops according to their lasting time, namely 1, 2, or 3 trimesters;
- Nutrients management (NM). This includes the management of N, P, and K under conventional or organic agriculture and also the practice of adding no nutrients to the soil;
- Nutrients and amendments distribution techniques (N/A D). This describes the choices in fertirrigation, soil incorporation, and foliar spray and also the practice of no nutrients and amendments distribution;
- Green manuring (GM). This variable is concerned with whether green manuring has been carried out or not;
- Amendments (A). These include biochar, compost, cow manure, chicken manure, leonardite, or their combinations as well as no amendment additions;
- Biomass (B). This highlights the use of green manuring, the incorporation of plant residues after food harvest, or the use of spontaneous plants and waste biomass;
- Crop type (CT). This includes break crops, start crops, and impoverishment crops;
- Soil coverage (SC). This describes the type of mulching used (plastic layer or cover crop);
- Irrigation (I). This considers drip, partial root zone drying, sprinklers, emergency drought systems, or no irrigation;
- Weeding (W). This includes hand and manual weeding or the use of a rototiller for weed removal as well as the use of mulching or cover cropping for weed control;
- Soil organic carbon evolution (ΔSOC). This is the target variable and is measured as the difference in SOC amounts before and after the application of agricultural practices and the food harvest. Furthermore, the SOC values were grouped into three classes to facilitate clarity and correct interpretation of the results. Specifically, the "NEGATIVE" class explains the reductions in SOC that are lower than $-0.5\ \mathrm{g{\cdot}kg^{-1}}$, the "NEUTRAL" class includes all the variations between -0.5 and $+0.5\ \mathrm{g{\cdot}kg^{-1}}$, and the "POSITIVE" class reports increments in SOC that are higher than $0.5\ \mathrm{g{\cdot}kg^{-1}}$.

2.2. The Decision Tree

The decision tree is an adaptable, flexible, and scalable data mining tool for decision making implemented through the definition of courses of actions and various outcomes [39]. It deals with complex problems and provides a visual representation that is easy to interpret [40]. The decision tree is applied more than other data mining methods in soil science thanks to its higher reliable results and lower interpretation bias, and it is most often used to map SOC levels and soil organic matter dynamics [41,42]. The decision tree has the shape of a flowchart, where a variable is examined within every step [43,44]. The items of the decision tree are nodes and branches. The nodes are classified into the following three different categories [45–47]: (i) The root node is intended as the first question, whereby a choice is made involving two options or more. It only shows outgoing edges. (ii) Child nodes result from splitting a node into new ones. As such, they are possible choices that become a specific level of the tree. For each child node, there is only one incoming edge and at least two outgoing edges. (iii) Leaf nodes show the final answer to a combination of decisions or events. These nodes do not split any further. As such, they have one incoming edge and no outgoing edges. A branch is a tree subsection that connects nodes; thus, a branch is a possible alternative at a specific point of the tree [39,46,48]. Every pathway that involves all the nodes identifies one classification rule, which is presented as an "if-then" rule. For example, "if condition 1 and condition 2 and condition . . . and condition k occur, then outcome j occurs" [45].

A decision tree is created by following three phases, namely splitting, stopping, and pruning. Splitting divides a node into at least two purer child nodes; the nodes' splitting order is determined by a parameter called purity [39]. There can be input variables that repeat several times across different levels of the tree, whereas certain variables cannot be included at all. This is because only the input variables related to the target variable are involved in splitting the nodes into purer child nodes [45]. The splitting ends when all child nodes are made of uniform records or upon meeting certain criteria for stopping or pruning [48]. There are several methods for performing the splitting based on decision tree algorithms, including information gain, gain ratio, the Gini index, normalized impurity-based criteria, the DKM criterion, and the Twoing criterion [48–50].

Stopping or pruning procedures are usually applied to avoid an overly complex decision tree. A stopping procedure determines when to end splitting [39] by using several parameters that are based on the research goal and the features of the dataset, i.e., the minimum number of records in a leaf or in a node before splitting as well as the number of steps of a leaf from the root node [45,50].

A pruning procedure reduces the size of a tree for better predictive accuracy. This is achieved by removing the child nodes that have low importance or classification magnitude [39], namely tree sections that may be based on inaccurate or incomprehensible data [49]. A further reason for using pruning is to obtain an accurate and simple description of the decision tree [48]. There are various pruning techniques according to the algorithm behind the decision tree; some of these examples include the following: reduced error pruning, minimum error pruning, error-based pruning, and optimal pruning [48].

Many decision tree algorithms have been developed over the last 30 years [44], including CHAID [51], CART [52], ID3 [53] (and its evolution C4.5 [35,54]), and conditional inference trees [55]. The algorithm used in this research is the C4.5, a milestone among decision tree algorithms [50] as it possesses the following general advantages: (i) it selects the most pertinent input variables for making a final decision; (ii) once relevant variables are identified, it identifies the key variables; (iii) continuous and discrete variables can be processed; (iv) it can work with missing data; and (v) it provides logical rules of classification [40,45].

Considering these general advantages together with the aim of the research, C4.5 was applied to identify clearly the most suitable combinations of practices leading to SOC increase. This was performed following the procedure proposed by Quinlan [54], Salzberg [56], and Wu et al. [57] as well as by using the software "Orange data mining" (version 3.36). Given the data collected and arranged in the dataset described above, the SOC variation was selected as a target variable, while the other variables were considered as input variables. Moreover, the specific C4.5 parameters set for building the decision tree were as follows: four records per node, gain-ratio method for the splitting procedure, and reduced error pruning for reducing over-fitting. Also, the confusion matrix was computed to define the classification performance of the algorithm through the calculation of the classification accuracy [50,58,59]. Generally, a classification algorithm performs well when this parameter is higher than 70% [60], while Ba'abbad et al. [61] highlighted that the application of the C4.5 algorithm for analyzing soil nutrients leads to reliable results with a classification accuracy of 68%.

3. Results and Discussion

3.1. Dataset Description

The distribution of the categorical values assumed by the 12 variables is summarized in Table 1. Generally, it is important to underline that the values classified as "No" mean the absence of that specific practice in an RFPC. Even though the crops were not clearly specified, their characteristics were considered in terms of crop duration and types through the variables "treatment duration" (TD) and "crop type" (CT). Indeed, the TD distinguished crops according to the time of management they took, and most of the considered RFPCs (66 out of 115) took three trimesters. The variable CT considered the crops' function in rotation; impoverishment effects on soil physical properties and soil organic carbon were found in 7 RFPCs, while beneficial effects were observed in 32 RFPCs.

Table 1. Distribution of the categorical values assumed by each variable reported as a percentage. These categorical values were based on the information gathered from the selected documents (Source: authors' elaboration from the 21 selected documents publicly available at the library of CIHEAM Bari).

Var.	Percentage Values	Var.	Percentage Values	Var.	Percentage Values
S	90%—Open field 10%—Tunnel	GM	82%—NO 18%—YES	SC	3%—Plastic layer 3%—Cover crops 94%—NO
TD	12%—1 trimester 30%—2 trimesters 58%—3 trimesters	A	3%—Biochar 28%—Compost 3%—Manure + compost 56%—NO 6%—Manure 2%—Chicken manure 2%—Leonardite	I	5%—Emergency 76%—Drip 3%—Drought 7%—NO 6%—Sprinkler 3%—Partial root zone drying
NM	34%—NO 49%—Organic 17%—Conventional	B	6%—Waste biomass 18%—Cover crop 1%—Spontaneous cover 75%—NO	W	48%—Manual 11%—Hand 20%—Rototiller 9%—NO 2%—Chemical 7%—Mulching 3%—Cover cropping
N/A D	31%—Fertirrigation 41%—Soil incorporation 1%—Foliar spray 19%—NO 8%—Fertirrigation + soil incorporation	CT	27%—Break crop 67%—Start crop 6%—Impoverishment crop	ΔSOC	13%—NEGATIVE 22%—NEUTRAL 65%—POSITIVE

Note: S = site; TD = treatment duration; NM = nutrients management; N/A D = nutrients and amendments distribution techniques; GM = green manuring; A = amendments; B = biomass; CT = crop type; SC = soil coverage; I = irrigation; W = weeding; and ΔSOC = soil organic carbon evolution.

"Site" (S) was another variable describing the agricultural conditions; only 12 RFPCs were carried out under tunnels. Regarding the variable "amendments" (A), the majority of the RFPCs were not amended, and the most used amendment was compost, despite the scarce number of RFPCs under conventional farming (19 out of 115) and the several RFPCs that did not supply any "nutrients management" (NM) to the crops (39 out of 115). Both amendments and fertilizers (the variable "nutrients and amendments distribution", N/A D) were distributed mostly by soil incorporation and fertirrigation (47 and 36 RFPCs out of 115, respectively).

Only 21 RFPCs were anticipated by "green manuring" (GM), whereas 29 RFPCs were anticipated by the use of "biomasses" (B), like waste biomasses, cover crops, and spontaneous cover (7, 21, and 1 RFPCs, respectively). Most of the RFPCs (107 out of 115) had no "soil coverage" (SC), the water was supplied (variable "irrigation", I) mainly by drip irrigation (87 out of 115 RFPCs), and "weeding" (W) was performed mostly by manual uprooting (55 out of 115 RFPCs). Furthermore, cover cropping was a possible value within different variables (biomass—B, soil coverage—SC, and weeding—W) and can be explained by the several advantages provided by this agricultural practice that can work for weed control [62], covering the soil [63], and soil improvement [64].

The initial SOC was, on average, 11 g·kg^{-1}, while the final one was 13 g·kg^{-1}. The highest initial SOC value was 11.8 g·kg^{-1} and the lowest was 6.7 g·kg^{-1}, while the highest and lowest final SOC values were 17.7 and 6.7 g·kg^{-1}, respectively (Figure 2A). The highest increase was 5.4 g·kg^{-1} and the highest decrease was equal to 3.4 g·kg^{-1}. The ΔSOC values led to negative impacts in 13% of the RFPCs, 22% of the RFPCs reported neutral values, while positive impacts were observed in 65% of the RFPCs (showed in Table 1 as a percentage and in Figure 2B as a number of RFPCs). Among the positive cases, the average increase was about 2 g·kg^{-1}, which is a good amount for agricultural soils but still little for a secondary succession under a Mediterranean climate [65].

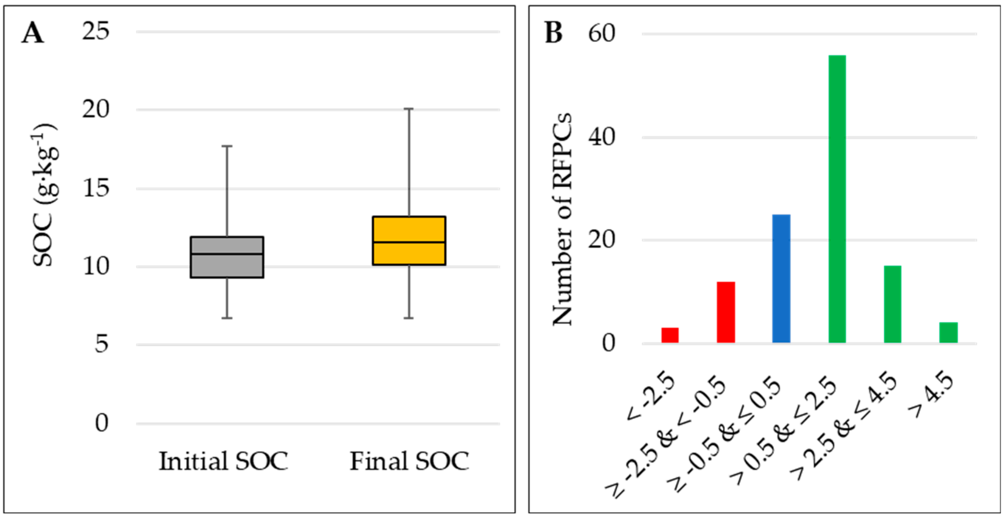

Figure 2. Box plot diagrams for the descriptive statistics of the initial and final SOC values: (**A**). The distribution of ΔSOC values (**B**) were distinguished according to their negative (red), neutral (blue), and positive (green) effects (source: authors' elaboration from the 21 selected documents publicly available at the library of CIHEAM Bari).

Despite the variation in the SOC being equal to 2 g·kg^{-1} perhaps appearing negligible (from the initial 11 g·kg^{-1} to the final 13 g·kg^{-1}), it also corresponded to 12 additional tons of soil organic carbon per hectare in a short period of time. Considering a price of permits on the European Union's carbon market that is equal to EUR 93 per ton of carbon (quoted on 19 July 2023), farmers may obtain an additional income of about EUR 1000 per hectare and for each crop [66].

3.2. Decision Tree Interpretation

The decision tree that resulted from the application of the C4.5 algorithm showed 3 main branches, 7 levels, and 30 nodes (Figure A1). Out of the 12 variables, 3 were not included, namely "site" (S), "green manuring" (GM), and "crop type" (CT). Specifically, the boxes (i.e., the leaves) in red indicate the negative SOC variation, the green and orange highlight the positive and neutral SOC variations, respectively, while the increasing color intensity indicates the "magnitude" of the SOC variation. There are also white boxes, representing negative, neutral, and positive SOC variations that were supported by up to 50% of the RFPCs.

The variable that primarily affected positive SOC variation (i.e., the root node) was "treatment duration" (TD) associated with 75 RFPCs out of 115; it generated three branches as the number of categorical values assumed by this variable. To understand this more in depth, the RFPCs lasting only one trimester showed negative SOC variation (10 RFPCs out of 14), while the RFPCs lasting two and three trimesters led to an increase in the SOC in 21 RFPCs out of 35 and in 52 RFPCs out of 66, respectively.

When focusing on the RFPCs lasting one trimester, the negative SOC variations occurred with no nutrients management (four RFPCs out of six) and when there was management under organic agriculture (six RFPCs out of eight). Despite the priming effect that rapidly hit the exogenous organic matter [67], the decomposition of easily soluble compounds may have occurred already after one month under Mediterranean climate conditions [68]. This could be the case because many other factors can interfere with this process. Indeed, Lehmann et al. [69] suggested that high molecular diversity, large spatial separation, and rapid temporal variability may slow down organic matter decomposition. This may explain why the SOC did not increase in cases where complex molecules were added (such as when additives were used in organic farming).

The SOC increases were recorded under a treatment duration (TD) that lasted two or three trimesters; this complied with the EU Common Agricultural Policy since the diversification of the crops as well as the extension of soil coverage were included among the greening practices inside direct payments [70]. Moreover, adopting RFPCs and a related crop management that lasts two or three trimesters in a long-term crop rotation will favor SOC increase and maintenance [71].

Among the RFPCs lasting two trimesters, the second key variable was "weeding" (W). In this regard, the most positive option in terms of SOC increase was the absence of weeding (6 RFPCs out of 6), followed by hand weeding (9 RFPCs out of 11), manual weeding (6 RFPCs out of 13), and the case of a rototiller labeled as neutral (since the SOC was not altered in 3 RFPCs out of 5). It is well known that the minimization of tillage may reduce SOC loss because of decreased oxidation [72–74]. This clearly explains our results from a completely positive SOC level to a neutral SOC level, achieved by the lack of weed management.

In the case of hand weeding, plants are removed and left on soil; thus, the decomposed plant biomass contributes to SOC gain in the case of conventional nutrients management, where rapidly available nutrients are provided [75]. When no nutrients management was performed, the SOC increases may have been determined by the soil disturbance [76]. Concerning manual weeding, the absence of weed uprooting made manual weeding comparable to mowing, and this was because both practices did not impact directly on the below-ground biomass; thus, the results can be compared with those of Malamataris et al. [77], who found an increase in SOC by using mowing.

Moreover, the presence of an irrigation system (variable "irrigation", I) together with manual weeding may explain the negative effect on SOC due to leaching [78] as well as the positive effect in the case of emergency irrigation that stimulates dissolved organic matter movement [79]. The positive effect of emergency irrigation on SOC could be explained by the occurrence of the Birch effect, and the mineralization of organic materials was likely triggered by the rewetting of the dry soil [80]. Finally, mechanical interventions, like the use of rototillers, had an effect on the SOC content, albeit only a minor one, as the larger soil aggregates were destroyed [76]. Although hand and manual weeding provided better SOC increases than using rototillers, it was not possible to suggest the use of these two practices to farmers that manage wide agricultural surfaces, despite the fact that both of them showed positive results at plot scale. Moreover, it should be considered that the use of rototillers in dry conditions may favor the wind erosion of soil. Thus, a comparison should be conducted between the absence of weed management and the use of rototillers, and the first one should be preferred. No tillage is applied to 4% of the EU's arable land [81,82], although this complies with the European Biodiversity strategy [83]. However, since the use of rototillers did not decrease SOC, it should be preferred over herbicides, which decreases SOC and whose use should be reduced in accordance with the EU Farm to Fork strategy [7,77].

When looking at the RFPCs lasting three trimesters, the irrigation technique (variable "irrigation", I) was the most important agricultural practice. In particular, the RFPCs that were irrigated with sprinklers and those without any irrigation at all were completely positive in terms of SOC increase (seven RFPCs out of seven and eight RFPCs out of eight, respectively). Also, the drip irrigation technique led to SOC increase, although this was only observed in 37 RFPCs out of 51. These findings are in line with Emde et al. [84], who noted that sprinkler and drip irrigation increased the SOC in the first 10 cm of soil depth by their direct effect on crop and non-crop plant biomass increase. In addition, other scholars have found that SOC oxidation is reduced in the case of no irrigation because of low microbial biomass presence or development [85]. Despite the SOC increases with drip irrigation (Figure A1), the practice was supported by less RFPCs when compared to the sprinkler method. Moreover, drip irrigation should be preferred for its implication with other European targets. Indeed, this system has a high water-use efficiency, especially when compared to sprinkler systems [86]. Furthermore, this efficient use complies with the aims of the EU Common Agricultural Policy in protecting water by ensuring and encouraging good management practices [87].

The SOC variation under drip irrigation was further explained by its combination with the variable "soil coverage" (SC). Plastic mulch did not increase SOC stock; indeed, certain pieces of research have reported a negative impact of plastic mulch on SOC content, and they have underlined that this is due to the temperature increases in the top layer of soil and the conservation of moisture, which are two important conditions for losses in SOC [88–91]. In hot climate conditions, the temperature under the plastic mulch increases to a point at which neither plants nor microorganisms will be able to settle or grow. According to Mo et al. [92], precipitation is the factor guiding the SOC's fate when under plastic mulching. The scarce precipitation in Mediterranean climates can explain the positive to neutral effects of soil coverage on the SOC observed in the decision tree. Furthermore, cover crops represented a strong positive influence on SOC increase (four RFPCs out of four), and they also complied with several other scientific works [93–96]. This may be due to the possible recruiting of beneficial soil microbiota, the improvement in soil aggregation or structure, and the addition of new organic matter [97].

The SOC variations under no soil coverage were further described by combinations with the variable "biomass" (B). In particular, a strong SOC increase was found in four RFPCs out of four, in which the waste biomasses were used directly on the soil, including olive mill wastewater, spent mushroom substrate, spent barley grain, and coffee chaff. Independently from their chemical nature, the impact of all these waste biomasses on the SOC was positive, and, according to the European Environmental Agency, they can easily enter the circular economy by reuse or recycling [98].

Also, no biomass addition led to SOC increases in 11 RFPCs out of 17. Within these cases, the organic material was supplied by compost. Indeed, the SOC variation under the no biomass addition condition was described further through its combination with the variable "amendments" (A). No amendment application had a neutral effect, while compost application determined a SOC increase in five RFPCs out of seven in only 9 months and in spite of the compost's recalcitrance to the decomposition [99]. In this case, three trimesters were sufficient for the increase in SOC because of the possible occurrence of the priming effect in the early months of application [100]. The compost was also undergoing a new valorization trend during the period of study since the European Commission has been looking at biodegradable plastics and packaging for their proper reuse in the composting process [101,102].

Moreover, the use of cover crops increased the SOC content in 15 RFPCs out of 21, which was further investigated trough the combination of the variable "nutrients and amendments distribution techniques" (N/A D). Cover crops, even if not incorporated into soil, led to an increase in the SOC in 100% of the RFPCs (six out of six), which could be due to the increased nutrient availability from the enriched microbial activities [103,104].

Soil incorporation registered a neutral influence on SOC increase in two RFPCs out of four. This can be explained by the difference between fertilizers and amendments, both of which are considered within this variable. However, it must be noted that amendments provide organic matter while fertilizers provide only nutrients [105].

The positive effect of fertirrigation (6 RFPCs out of 10) was strictly dependent on the management of the main nutrients (variable "nutrients management", NM). In the case of fertirrigation under conventional agriculture, no influence on the SOC content was found in four RFPCs out of six. This was because the fertilizers were synthetic and were supplied independently from their organic or inorganic chemical nature. On the other hand, fertirrigation under organic agriculture led to SOC increases in all of the RFPCs since the compost tea brought organic compounds together with nutrients [106]. This finding is in line with the target of the European Green Deal regarding the increase of 25% in organically farmed agricultural land by 2030 [107].

The classification rules were extracted after the creation of the decision tree. These rules provided a linguistic interpretation of the decision tree, thereby becoming a valuable support through which to understand the combination of agricultural practices that lead to SOC increase and decrease. Table 2 shows some of the exemplary rules related to the highest negative and positive SOC variations. The rules are based on a unique structure, in which the root and child nodes are listed at the beginning of the rule (If condition. . .), whereas a specific leaf node is listed in the second part (then class . . .). For example, the classification rule describing the most negative SOC variation (rule no. 1) should be interpreted as follows: "If the treatment duration is equal to 1 trimester and the nutrients management is performed under organic agriculture, then the SOC variation is NEGATIVE". In the same way, the rule describing the most positive SOC variation and including the highest number of agricultural practices (rule no. 9) should be read as follows: "If the treatment duration is equal to 3 trimesters, water is supplied by drip irrigation, there is no soil coverage, biomass is incorporated into soil through a cover crop, the nutrients and amendments distribution is carried out through fertirrigation and the nutrients management is performed under organic agriculture, then the SOC variation is POSITIVE".

Table 2. The exemplary classification rules related to the highest negative and positive SOC variations.

Rule No.	If Condition	Then, ΔSOC Class
1	treatment duration = 1 trimester AND nutrients management = organic	NEGATIVE
2	treatment duration = 2 trimesters AND weeding = NO	POSITIVE
3	treatment duration = 2 trimesters AND weeding = hand AND nutrients management = NO	POSITIVE
4	treatment duration = 3 trimesters AND irrigation = NO	POSITIVE
5	treatment duration = 3 trimesters AND irrigation = sprinkler	POSITIVE
6	treatment duration = 3 trimesters AND irrigation = drip AND soil coverage = cover crops	POSITIVE
7	treatment duration = 3 trimesters AND irrigation = drip AND soil coverage = NO AND biomass = waste biomass	POSITIVE
8	treatment duration = 3 trimesters AND irrigation = drip AND soil coverage = NO AND biomass = cover crop AND nutrients and amendments distribution techniques = NO	POSITIVE
9	treatment duration = 3 trimesters AND irrigation = drip AND soil coverage = NO AND biomass = cover crop AND nutrients and amendments distribution techniques = fertirrigation AND nutrients management = organic	POSITIVE

Finally, the confusion matrix computed by "Orange data mining" is reported in Table 3. This enabled us to calculate the accuracy of the classification of the C4.5 algorithm in relation to the dataset as a ratio between the correct classified RFPCs (into the diagonal of the matrix) and all of the RFPCs [58]. The matrix rows include the RFPCs in an actual class, whereas the columns report the RFPCs in a predicted class [59]. Table 3 shows that the classification accuracy was equal to 0.73, which means that 73% of the RFPCs were classified correctly in terms of SOC variation. In particular, matches between the predicted and actual negative ΔSOC class were observed in 13 RFPCs out of 15 (86.6%), and correspondence between the predicted and actual neutral ΔSOC class was found in 6 RFPCs out of 25 (24%); meanwhile, correspondence between the predicted and actual positive ΔSOC class was found in 65 RFPCs out of 75 (86.6%). These results suggested that the C4.5 algorithm performed an overall reliable classification; thus, the results are valid particularly for negative and positive ΔSOC. The lower classification performance related to neutral ΔSOC may be explained by the fact that this class included both negative and positive values (from -0.5 g·kg^{-1} to +0.5 g·kg^{-1}).

Table 3. The confusion matrix. Each column reports the RFPCs in a predicted ΔSOC class, while each row includes the RFPCs in an actual class. Correct classified RFPCs are reported in the diagonal.

		PREDICTED			
		Negative	**Neutral**	**Positive**	**Tot.**
ACTUAL	**Negative**	13	2	0	15
	Neutral	7	6	12	25
	Positive	4	6	65	75
	Tot.	24	15	76	115

4. Conclusions

In this research, 115 real food production cases (RFPCs) were carried out over a period of 20 years in the same pedo-climatic conditions. The RFPCs were investigated for the purposes of understanding the effects and the roles of different combinations of agricultural practices on SOC variation. Twelve variables were identified, and the resulting dataset was processed through the C4.5 algorithm. Treatment duration was identified as the first factor that affects SOC; however, when excluding the RFPCs that took one trimester, the differences between the practices and their combinations on SOC content could be inferred. The RFPCs with the highest increase in SOC were recorded for the nutrients distributed by fertirrigation under organic management, and the practices that mostly affected SOC positively were cover crops and drip irrigation. On the other hand, the practices that negatively affected SOC were found within weed management run by rototillers and when manual weeding was combined with drip irrigation.

The dataset description was mandatory for running and interpreting the decision tree; however, it should be noted that these RFPCs are examples through which one can validate the method for future uses in different contexts. Besides the specific results, this approach can be replicable, adaptable, scalable, and designed for farmers, thereby supporting them in the transition to new and more sustainable management strategies. The proposed method differs from the previous pieces of research since it relies on a bottom–up approach that offers farmers and stakeholders the opportunity to design management strategies that mostly address their specific needs while not neglecting SOC increase. Indeed, from the farmers' point of view, it is important to underline that the approach can support them to look at previous food production experiences and to define new combinations of practices for increasing SOC. Moreover, the flexibility of the proposed approach may enable farmers to create tailored strategies, including other factors or constraints, such as feasibility, economic convenience, mechanical availability, and law restrictions, which can be included as additional variables through which to analyze a decision tree.

From a wider perspective, this research can serve as guidance to help EU private actors and public authorities to start up carbon farming initiatives, pilot projects, or certification schemes at local and/or regional levels. Indeed, EU policies and funding programs are crucial instruments for bringing about widespread carbon farming. For instance, the approved CAP 28 Strategic Plans expect to incentivize carbon farming through eco-schemes aimed at soil conservation. Also, the Circular Economy Action Plan within the European Green Deal promotes the diffusion of carbon farming in terms of carbon uptake and circularity, and this is to be achieved through the development of a regulatory framework for the certification of carbon storage. In the same way, EU programs like Horizon, LIFE, and Interreg can fund projects that are aimed at fostering carbon farming through several activities such as the following: the development of approaches for assessing and monitoring SOC at the farm level; the development of certification schemes for food produced through farming practices that improve SOC; the organization of training programs for farmers, advisers, and public–private actors regarding the practices that one has to adopt for increasing SOC and the related benefits; the creation of European networks of farmers and actors for replicating project results and tools; and the development of a voluntary carbon market that is based on carbon stored at the farm level. Besides the environmental and economic benefits, changing to farm management practices that are oriented toward increasing carbon storage may trigger some social co-benefits, such as improved interactions between farmers for the purpose of knowledge sharing via a perspective of a "community of practice" as well as through the major involvement of advisers, technicians, and suppliers for the effective implementation of certain farming practices (e.g., irrigation, use of biomass for soil coverage, weeding, nutrient and amendment distribution, etc.).

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Appendix A

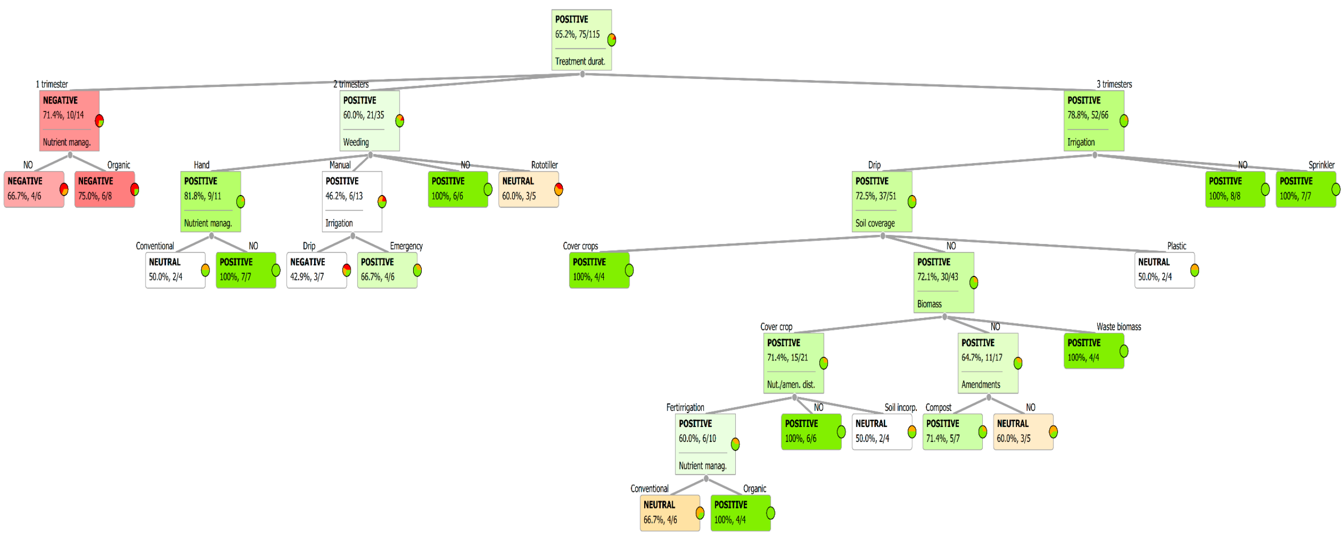

Figure A1. The decision tree obtained from the C.4.5 algorithm. The pie chart of each box indicates the shares of negative, neutral, and positive ΔSOC.

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