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Carbon Farming: Bridging Technology Development with Policy Goals

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Abstract: This paper conducts an in-depth exploration of carbon farming at the confluence of advanced technology and EU policy, particularly within the context of the European Green Deal. Emphasizing technologies at technology readiness levels (TRL) 6–9, the study critically analyzes and synthesizes their practical implementation potential in the agricultural sector. Methodologically, the paper integrates a review of current technologies with an analysis of EU policy frameworks, focusing on the practical application of these technologies in alignment with policy directives. The results demonstrate a symbiotic relationship between emerging carbon farming technologies and evolving EU policies, highlighting how technological advancements can be effectively integrated within existing and proposed legal structures. This alignment is crucial for fostering practical, market-ready, and sustainable agricultural practices. Significantly, this study underscores the importance of bridging theoretical research with commercialization. It proposes a pathway for transitioning current research insights into innovative, market-responsive products, thereby contributing to sustainable agricultural practices. This approach not only aligns with the European Green Deal but also addresses market demands and environmental policy evolution. In conclusion, the paper serves as a critical link between theoretical advancements and practical applications in sustainable carbon farming. It offers a comprehensive understanding of both the technological and policy landscapes, aiming to propel practical, sustainable solutions in step with dynamic environmental policy goals.

Keywords: advanced sensing techniques; AI; carbon credits; soil carbon sequestration

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1. Introduction

The 2023 report of the United Nations Intergovernmental Panel on Climate Change highlights the fact that current efforts to limit global temperature rise to 1.5 °C are not sufficient. This report, the year 2019 was utilized as the baseline for analysis, states that emissions need to be decreased by 43% by 2030 to meet the Paris Agreement goals. Much more effort is needed imminently to achieve these goals [1].

At the end of the previous century, as a means for decreasing CO_2 emissions, economists proposed the development of carbon markets since financial incentives have historically been proven as a very good vehicle for achieving goals. This was put on a path to realization after the Kyoto Protocol was signed. In a simplistic way, the main principle behind this is to ensure that for every tonne of CO_2 emitted somewhere, another tonne of CO_2 emissions is captured elsewhere. The clean development mechanism (CDM) was the first carbon market scheme to be realized back in 2006. In essence, richer countries could logistically reduce their emissions by paying for the development of carbon-lowering projects in developing countries and accounting them in their own targets. In response, the EU set up the European Union Emissions Trading System (EU ETS). A study prepared for DG Clima in 2016 stated that "*. . .85% of the covered projects and 73% of the potential 2013–2020 certified emission reductions (CERs) supply have a low likelihood of ensuring environmental integrity (i.e., ensuring that emission reductions are additional and not over-estimated). Only 2% of the projects and 7% of CER supply have a high likelihood of ensuring environmental integrity. The remainder, 13% of the projects and 20% of the potential CER supply, involve a medium likelihood of ensuring environmental integrity. . . our analysis suggests that the CDM's performance as a whole has anything but improved, despite improvements of a number of CDM standards. The main reason for this is a shift in the project portfolio towards projects with more questionable additionality. . .*" [2]. Still and despite the low carbon prices and the aforementioned problems and challenges, the EU ETS managed to reduce carbon emissions by more than 1 bn t $CO_{2(eq)}$ between 2008 and 2016 [3].

On 1 January 2021, the 4th Phase of the EU ETS commenced, with the EC planning a review of the 2018 Directive by 2026. Since 2018, prices have continuously increased, exceeding in February 2023 the 100 EUR/t $CO_{2(eq)}$ mark. In the "Fit for 55" package the EC proposes to increase the EU ETS reduction target for 2030 to −61% compared to 2005. Such a target is expected to increase the scarcity of EU Emission Allowances (EUAs) leading to a considerable increase in prices up to 129 EUR/t $CO_{2(eq)}$ [4]. The European Investment Bank (EIB) in "EIB Group Climate Bank Roadmap 2021–2025" which was published in November 2020 proposed a new methodology for calculating the shadow cost of carbon (EIB uses an economic (shadow) price of carbon to convert changes in tonnes of GHG into euros) reaching 800 EUR/t $CO_{2(eq)}$ in 2050 as is presented in Figure 1 (the values are in EUR of 2016) [5].

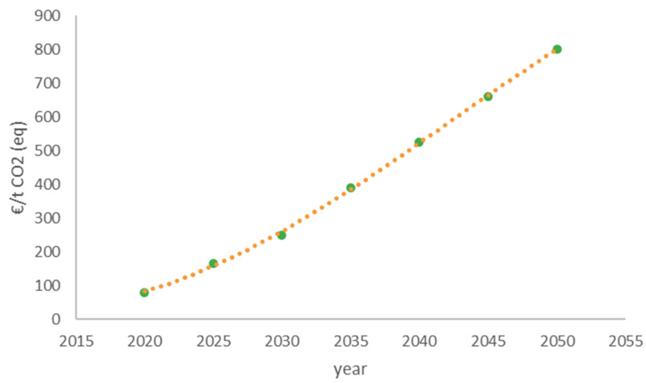

Figure 1. Evolution of the EIB shadow cost of carbon for the period 2020–2050 (base value: EUR of 2016 value) [5].

The price of carbon has a strong link with financing, and especially when projects present carbon negativity, CO_2 credits can and need to be sold to improve the financial outlook and profitability of these projects. This paper aimed to navigate the complex domain of carbon farming, not as a comprehensive review, but as a pivotal exploration in the context of technology development policy. While it references a broad spectrum of research papers, its core strength lies not in reiterating existing knowledge, but in critically analyzing and synthesizing the current state of technology, particularly those at technology readiness levels (TRL) 6–8. By intertwining the policy and legal frameworks of the European Union on carbon farming with cutting-edge technological advancements, the aim of the paper was to chart a pragmatic and forward-thinking path for technology development. This approach was meticulously designed to not only respond to market demands but also to align with the ambitious targets of the European Green Deal. Consequently, this paper serves as a crucial bridge between ongoing research, technology development, and commercialization, underscoring the potential of integrating current research insights to foster the creation of innovative products. This endeavor aims not just at theoretical advancement, but at catalyzing practical, sustainable solutions in carbon farming that are in step with evolving environmental policy goals.

2. Carbon Capture and Storage

In general, carbon credits can be issued by any project that can reduce, avoid, destroy, or capture emissions. This is directly related to CO_2 capture and storage, which can take place as follows:

- CO_2 capture In specific production pathways CO_2 can be captured at the plant which has CO_2 as a side product of its process [6], or by a specially designed plant that directly captures CO_2 from the air [7]. This can be either reused or sequestered. The captured CO_2 can be biogenic, from fossil fuels, or from direct air capture.
- Geological Carbon Sequestration: CO_2 is captured and stored in geological formations actively contributing to reaching the set climate goals [8].
- Biological Carbon Sequestration, which comes in three forms:
    - Soil Carbon Sequestration: This is mostly related to agriculture. Sequestration of carbon in the ground takes place through the process of photosynthesis. The carbon storage in the earth is in the form of organic carbon (SOC) or carbonates. Usually, it is accomplished by properly chosen crop rotation which minimizes the loss of carbon from the ground along with adding manure, cover cropping to improve soil structure, adding organic matter, and finally, conservation tillage practices that enhance water use efficiency, reduce soil erosion, and increase carbon sequestration in the topsoil.
    - Ocean Carbon Sequestration: As in geological carbon sequestration, CO_2 is captured and is then injected directly into water forming bicarbonates [9].
    - Forest Carbon Sequestration. This is related to forestry. By utilizing appropriate practices (e.g., thinning followed by prescribed burning) sequestered CO_2 accumulation can be increased in the form of forest soil, litter, biomass, and deadwood [10].

3. Carbon Farming

The Farm to Fork Strategy is an integral part of the EU comprehensive plan to achieve carbon neutrality by 2050. It sets radical goals to transform the EU food system, with a significant emphasis on sustainable practices and reducing the environmental and carbon footprint of food production and consumption. Under this strategy, the EU aims to reduce the use of chemical pesticides by 50%, decrease nutrient losses by at least 50% while ensuring no deterioration in soil fertility, and reduce the use of fertilizers by at least 20% by 2030. These ambitious targets are designed to facilitate a systemic change in agricultural practices, aligning them with environmental sustainability. Moreover, the strategy envisions a significant increase in organic farming, covering 25% of agricultural land by 2030, thus fostering biodiversity and reducing the agricultural sector's carbon footprint.

In this transformative context, carbon farming emerges as a key component. Carbon farming can be defined as a farm management system where methods are utilized to achieve the sequestration of atmospheric carbon into the soil and in crop roots, wood, and leaves. The overall objective is to remove CO_2 from the atmosphere and store it in the soil for the long term [11,12].

The European Commission has adopted the Communication on Sustainable Carbon Cycles in line with the Farm to Fork Strategy. This communication outlines the actions targeting at mainstreaming carbon farming as a green business model. The main measures included are as follows [13]:

- The promotion of carbon farming practices under the Common Agricultural Policy (CAP) and other EU programmes

- Activities promoting the standardization of monitoring, reporting, and verification methodologies.

The main carbon farming practices for cropping are the following [14–17]:

- Adopt no-till cropping practices: Soil disturbance by any means and especially tillage leads to breaking up of soil aggregates, organic matter, and biochemical structures. It increases the risk of soil erosion and GHG release. These can be avoided with no-till practices, whereby improving SOC sequestration and soil structure. It is important to underline that no-till practices alone do not account for SOC sequestration, but they are important for systematic carbon farming approaches that also incorporate other practices [18].
- Apply biochar: Biochar is derived from pyrolysis or gasification of organic material and its application is basically direct carbon application with most of the carbon content being absorbed in the short term of the carbon cycle. It enhances soil fertility and stability, SOC sequestration, and water retention. It is a low-cost choice and it is environmentally friendly [19].
- Apply mulch to bare soil: Bare soil, as heavily tilled soil too, is prone to wind and water erosion reducing topsoil SOC content. Practices like mulching in the form of cover crops, crop residues, composting, etc., prevent erosion and enhance SOC sequestration by establishing biochemical structures and increasing microbial activity, soil structure, and nutrient cycling. They also help with soil water retention and lowering the mean soil temperature [20].
- Establish areas of native vegetation: Establishing areas of native vegetation as a form of carbon farming primarily contributes to carbon sequestration, where the inherent compatibility of native vegetation with local conditions leads to robust growth and enhanced carbon absorption during photosynthesis. This not only sequesters carbon in plant tissues but also improves soil health through robust root systems that retain soil structure and prevent erosion, creating a conducive environment for nutrient cycling and further soil carbon sequestration. The promotion of biodiversity is another significant benefit, as native vegetation provides habitats for local fauna, contributing to a more resilient ecosystem and a healthier soil microbiome. Additionally, native vegetation plays a role in local water cycle regulation, affecting the soil's ability to store carbon through its water retention capacity. Moreover, the reduced input requirements for native vegetation, such as the reduced requirements for water, fertilizers, and pesticides, contribute to lower greenhouse gas emissions associated with the production and application of these inputs, making it a more sustainable choice [21].
- Inter-crop with perennial pastures: Avoiding monocultures and establishing biodiversity with crop rotations of polycultures accompanied by native vegetation reducing areas of bare soil to the minimum, leads to cultivation of a field scale ecosystem. Moving in this direction means reaping the benefits of regenerative agriculture with microbial biomass and root networks increasing soil health, fertility crop yield, and SOC sequestration, while also avoiding erosion [22].
- Plant perennial pastures: Cropping perennial pastures entails cultivating perennial grasses with deep root systems that enhance soil-carbon sequestration, improve soil structure, and prevent erosion. These grasses capture atmospheric carbon dioxide, significantly reducing carbon release back into the atmosphere. Additionally, perennial pastures foster soil microbial activities essential for nutrient cycling, aiding further in carbon sequestration. They also promote local biodiversity, providing habitats for various organisms, which in turn supports a more resilient ecosystem conducive for long-term carbon sequestration. Moreover, being resilient to environmental stressors, perennial pastures require reduced inputs like water, fertilizers, and pesticides, thus reducing associated greenhouse gas emissions [23].
- Plant tree belts: Except from the aforementioned benefits, tree belts also offer wind protection for the crops, they lower the mean soil temperature by providing shade, they improve the biodiversity of the fields, and provide a habitat for various organisms [24].

- Plant trees for harvest: Planting trees for harvest, such as oil mallee, engages in carbon sequestration during growth, while improving soil health through enhanced structure and erosion prevention. This practice supports local biodiversity, contributing to a more resilient ecosystem. The harvested products like oil serve as renewable resources, potentially reducing reliance on fossil-based products. Additionally, the lower input requirements compared to conventional crops, reduce associated greenhouse gas emissions. Through a managed harvesting and replanting cycle, this practice can provide sustainable income and resources alongside environmental benefits [25].
- Retain stubble after crop harvest: Stubble retention reduces soil erosion, helps with water retention and infiltration while enhancing nutrient and carbon input. Its impact is even greater when combined with other practices and in general it enhances plant diversity leading to more carbon being sequestered. The results depend on the quality of the carbon input but in any case, stubble retention improves soil health [26].

Table 1 presents a summary of the literature review results performed in this section highlighting the key findings, gaps identified, and relevance.

Table 1. Summary of literature review findings of Section 3.

Reference	Key Findings	Gaps Identified	Relevance
[11,12]	Defined carbon farming as a farm management system aiming at the sequestration of atmospheric carbon.	Detailed impact assessment of different carbon farming practices on various soil types and climates.	Provides a definition of carbon farming to be used as a base, aligning with the paper's focus on bridging technology and policy.
[13]	Outlines EU actions for mainstreaming carbon farming as part of the Sustainable Carbon Cycles Communication.	Need for more comprehensive policy frameworks that integrate economic, environmental, and social aspects.	Highlights the policy background against which the paper's recommendations are made.
	Describes main carbon farming practices for cropping, such as no-till practices, biochar application, and mulching.	Comparative analysis of the effectiveness and scalability of different carbon farming practices.	Forms the basis for discussing the technological aspects of carbon farming practices in the EU context.

4. Measuring Soil Carbon Sequestration

Carbon stock in soil encompasses both organic and inorganic carbon. The latter, soil inorganic carbon (SIC), exists as carbonate minerals within the soil. Soil organic carbon (SOC), on the other hand, is found in the following two forms: as fresh plant matter, which is readily available SOC, and in the form of humus or charcoal, known as inert SOC. Current research studies predominantly concentrate on the sequestration of SOC. Soil carbon acts as a significant carbon sink, capable of capturing and storing carbon which would otherwise contribute to atmospheric CO_2 levels. SOC typically retains carbon for several decades, a duration influenced by decomposition rates, whereas SIC has the capacity to sequester carbon for over 70,000 years. Methods commonly employed for SOC sequestration primarily involve land management strategies, including planting perennial crops, retaining plant residues and compost, minimizing tillage, and adopting varied agricultural practices specific to different regions.

4.1. Traditional Methods

The recommended calculation for changes in SOC stock is to multiply organic carbon measurements with bulk density measurements for a fixed depth of 0–30 cm. The result of this calculation should then be reported as the mass of carbon per unit area, usually t $[CO_{2(eq)}]$ ha^{-1} [27]. Traditionally, in detail the steps to be followed for estimating the soil carbon sequestration are the following [28]:

- Sampling design—stratification of the farm
- Sample collection

- Sample preparation and analytical methods
- Quantification of SOC stocks
- Scaling SOC stocks to landscape and whole farms.

Stratification is very important and key to the overall quantification of soil carbon stocks and can be affected by various parameters, including agricultural productivity, economic outputs, potential GHG emissions, and social and cultural values [29]. After the points from where samples will be collected have been specified, traditionally samples are taken by hand using a steel corer since most arable lands do not contain a large amount of rocks. The samples need to be collected at least at 0–10 and 10–30 cm depth intervals, while it is good to take samples in the 30–50 cm depth, if feasible. In literature, it is proposed to take fewer samples at the 30–50 cm depth due to the difficulties faced in obtaining them. The samples are then sent to a soil laboratory where by using standardized dry combustion or wet oxidation, SOC can be measured.

4.2. Emerging Methods

The process described above is time consuming, labor consuming, and costly. There are several emerging alternative methods aiming to address these shortcomings. These can be categorized as follows [30–32]: spectroscopy; eddy covariance and carbon flux; remote sensing; and electrical conductivity.

4.2.1. Spectroscopy

The theoretical base of spectroscopy approaches is based on the soil diffuse reflectance property. This, in turn, depends on soil composition, particle size distribution, organic matter, iron oxides and carbonates present, and soluble salts in the soil [33]. Reflectance spectroscopy for SOC estimation appears to have many advantages compared to lab measurements in terms of cost-effectiveness, ease of use, and reliable repeatability, aiding in the construction of large soil libraries [34]. Multiple types of spectroscopy have been used for soil carbon measurement like visible [35] and near-infrared (Vis–NIR) [36,37], mid-infrared (MIR) [37], laser-induced breakdown spectroscopy (LIBS) [38], inelastic neutron scattering (INS) [39,40], X-ray fluorescence (XRF) [41], and γ-ray spectroscopy [42]. Vis–NIR is currently considered to be one of the most promising methods due to the relatively high accuracy and in-field use capabilities [30]. The same conclusion was reached in a study where a hyperspectral optical sensor was used, and the most important spectrum was 400–700 nm (Vis) for SOC prediction [43]. Enhanced results have been achieved with data fusion of visible spectrum data, RGB digital camera data, and sentinel 2 bands with the use of machine learning [44]. Other fusion attempts were made between MIR and XRF and the resulting model results did not surpass the individual models [45]. On the other hand, the combination of Vis–NIR and the XRF model produced superior results in SOC estimation compared to the individual models [46].

In any case, the accuracy of the results depends heavily on the processing techniques. A study of Vis–NIR–SWIR spectroscopy, with the use of three spectrometers in four field and lab setups, underlines the importance of the ISS spectral alignment method, for direct comparability of data [47]. Other studies also focused on Vis–NIR [48] and MIR [49] data pre-processing methods.

The spectroscopy methods can be utilized in mainly three ways. The first method consists of obtaining the samples in the field in the traditional way and then using a spectrometer in the laboratory; the second method is to use a portable spectrometer in the field; the third is the use of spectrometer sensor assemblies in the soil. A performance assessment between a fixed position MIR, a portable MIR, and portable Vis–NIR device data, processed by the Cubist ML algorithm was carried out [50]. Fixed position MIR gave the most accurate results, but the portable Vis–NIR device was the most cost-effective for the field-scale use. Portable NIR spectrometers currently cost in the range of a few thousand euros in terms of hardware, but still face maturity issues especially when used by non-experts [51].

4.2.2. Eddy Covariance and Carbon Flux

This method measures carbon fluxes in the atmosphere around agricultural lands and in areas where there is a considerable carbon exchange between the air and the soil [52–54]. The method can be used for large areas and presents challenges in its application for small farm level measurements. As stated in [55] spatial carbon flux variations under 20 m cannot be traced. Other challenges have also occurred in the multi-year dataset from EC in [56] with sensor drift due to dirt, sensor self-heating, and high wind speeds among them. All these sources of uncertainty add-up in the long-term, demanding reoccurring calibration, data filtering, and data gap filling (due to quality flags). At the same time, however, when eddy covariance data are correlated with other data, such as farm management data, more accurate measurements can be obtained [57].

4.2.3. Remote Sensing

Remote sensing was first used to measure soil carbon in larger areas. Optical sensors that can capture object wavelengths in the visible, near infrared, and shortwave infrared spectral regions mounted on airborne (aircrafts and drones) or spaceborne (satellites) platforms can provide sufficient data (bands and indices) for measuring soil carbon especially when coupled with artificial intelligence (AI) and machine learning (ML) techniques [58].

Specifically, on airborne platforms, there are sensors mounted either on aircraft or more commonly on unmanned aerial systems (UAS). Examples of aircraft-based platforms are APEX and HyMap. In [59] HyMap acquired data were used for field-scale SOC predictions for various surfaces. In [60] Apex hyperspectral data were used along with local soil datasets and sentinel 2 data. The study shows that the CAI index from APEX and the NBR2 index from sentinel 2 highly correlate with crop residue cover in the field that affects the SOC prediction and therefore, appropriate thresholds can be applied. On the other hand, many studies have been conducted to assess the suitability of UAS-mounted sensors for SOC prediction. In [61], UAV hyperspectral data along with a lab-derived hyperspectral dataset were evaluated for field scale SOC prediction and the results suggested the optimal band selection for this specific use. Other attempts, examined the use of UAV hyperspectral data and soil-library data as an alternative to field sampling [62] as well as the use of UAV multispectral Vis–NIR data from 120 m altitude and 12 cm spatial resolution achieving $R^2 = 0.95$ and RMSE = 0.21% on the validation of the model [63]. Although the use of airborne platforms is quite promising (large cover, easier flight repetition), the ease-of-use, availability, and archived data of spaceborne platforms make up the factor that defines them as the most popular choice. Landsat imagery-derived indices for SOM estimation [64], LAI derived by MODIS imagery and a SOC model data for SOC estimation [65], SOC estimation with indices derived from sentinel 2 imagery [66,67], and SOC and bulk density estimation based on SAR data from sentinel 1 along with a structural equation model [68] are just a few examples.

Many studies have examined the effect of various indices and other data as predictors on SOC estimation. The NBR2 (correlates with soil moisture) and NDVI (correlates with vegetation) thresholds from sentinel 2 have also been examined for noise removal and better accuracy in [69]. In another study, Landsat-8 derived indices were characterized as weak predictors, while soil structure, geographic features, weather data, and BI were characterized as stronger predictors [70].

This underlines the importance of combining satellite data with stronger predictors and other sources. For example, the use of sentinel 2 data along with GIS [71], the fusion of sentinel 1 and sentinel 2 data [72], and the fusion of sentinel 1, sentinel 2, and DEM [66–70,73–76].

4.2.4. Electrical Conductivity

The measurement of electrical conductivity of soils has been tested for many years with non-contact and Coulter-based sensors [77] and it has been an invaluable tool with multiple applications in precision agriculture [78,79]. There are references in the relevant literature that electrical conductivity could also be used to estimate soil carbon [80], especially with low soil salinity. In the study of [81] no direct correlation with SOC content was found but the EC readings could be valuable for improved SOC spatial estimation. While EC levels cannot be quantified precisely, their relative differences are useful as ancillary data, in a relative sense, when combined with other information such as soil texture, land use, and soil salinity [82]. Since electrical conductivity is used extensively to measure/estimate multiple soil parameters and at the same time low cost sensors or even non-contact sensors are currently deployed, electrical conductivity could be used in soil carbon measurement approaches utilizing multiple techniques [30]. An approach for predicting clay and SOM content with the combination of electrical conductivity and RGB imagery was made [74,83] providing a simple and promising method without soil sampling. Some other examples are the combination of EC data and a γ-ray spectrometer for field-scale soil property estimation [38], as well as with ground-penetrating radar (GPR) for field-scale SOC estimation [84]. It is worth mentioning that with the use of machine learning, predictions of EC itself and SOC content can be made by providing data from extensive soil libraries [85]. This study was an attempt to produce a data-driven prediction model with the physical attributes that affect the predictions being more transparent. Originally, for this purpose, there are model-based predictions, where a plethora of SOC models can be used [86].

4.2.5. Soil Organic Carbon Modelling

To sum up all the above, there are various methods such as laboratory spectroscopy, in situ measurements, airborne hyperspectral and multispectral imagery, spaceborne hyperspectral and multispectral imagery, etc. but there is not a cost-effective and sufficiently rapid way for direct SOC measurements, even on the field-scale. What is more, there are many studies that state the importance of various chemical and biological indicators that affect SOC content [87]. Carbon inputs, climate, soil carbon pools, and soil properties play a significant role in the rate of change of SOC sequestration [88] together with elevation, slope, and vegetation type [89] as well as land use and management in exogenic factors [90]. As many as possible of the above indicators must be considered in order to produce a model that can provide accurate estimations of SOC content. Many approaches have been made in the past for SOC modelling [91] and a variety of options is available today or even validated [86] but their accuracy in most cases cannot be compared to data-driven approaches, although, they can be used as a component of stochastic filtering methodologies such as Kalman filtering [92,93]. On the other hand, there are plenty of data-driven approaches in order to find the relationship between ancillary data and SOC content. A study tested the use of ANN, SVM, MLR, and RF methodologies with RF being the most accurate [94], while in another study RF, XGBoost, and RFRK methodologies were compared with RFRK showing the best results and XGBoost also being very promising on the local scale [95]. Another study between PLSR, RF, KNN, ANN, CNN, and LSTM stated that LSTM and CNN following, showed the best results but their training requires large datasets [96]. Finally, other deep learning routes have been explored [97,98] showing also promising results but as it stands more studies should be conducted in order to define the most suitable configuration of collected data and ML/DL algorithms as there are plenty of them available to be studied [87].

Table 2 presents a summary of the literature review results performed in this section highlighting the key findings, gaps identified, and relevance.

Table 2. Summary of literature review findings of Section 4.

Reference	Key Findings	Gaps Identified	Relevance
[27,28]	Describes traditional methods for SOC stock calculation and steps for estimating soil-carbon sequestration, emphasizing sampling design and preparation.	The need for more efficient, less labor-intensive methods for large-scale SOC measurement.	Highlight traditional methodologies as a baseline for discussing advancements in carbon sequestration measurement.
[30–32]	Introduces emerging methods such as spectroscopy, eddy covariance, remote sensing, and electrical conductivity, aiming to address shortcomings of traditional methods.	Exploration of the accuracy and practical application limits of these emerging methods in diverse environmental settings.	Provide a comprehensive overview of current innovations in SOC measurement, crucial for the paper's focus on technological advancements.
[33–46]	Discusses various types of spectroscopy used for soil carbon measurement, such as Vis–NIR, MIR, and XRF, and their advantages in cost-effectiveness and repeatability.	Detailed comparison of different spectroscopy methods in terms of accuracy, ease-of-use, and cost for practical applications.	Support the paper's exploration of cost-effective and efficient technologies in carbon farming.
[52–57]	Eddy covariance method outlined for measuring carbon fluxes, highlighting its use for large areas but noting challenges in small-scale application.	Need for refinement in sensor technology and data processing to enhance accuracy, especially for small-scale farms.	Aligns with the discussion on scalable and adaptable measurement technologies in carbon farming.
[58–76]	Description of remote sensing techniques utilizing various platforms and sensors for soil-carbon estimation, often coupled with AI and ML techniques.	Further research into AI algorithms for remote sensing and data fusion techniques between remote and local sensing methods for more accurate SOC estimation with lower cost.	Illustrates the intersection of remote sensing technology with AI, relevant to the paper's theme of integrating cutting-edge technology with carbon farming.
	Explores the use of electrical conductivity in soil carbon estimation, highlighting its potential when combined with other techniques.	Investigation into the direct correlation of EC readings with SOC content across different soil types and conditions.	Adds to the paper's discussion on multi-faceted, innovative approaches to soil-carbon measurement.

5. From Research to Market

There are many prisms under which carbon farming can be seen. First, from the environmental point of view, soil holds quite a large amount of carbon stocks and this needs to be maintained this way. What is more, the potential of enhanced carbon sequestration is helping, in a way, to tackle GHG offsets. From the agricultural point of view, the amount of carbon that was released from the topsoil until now, can be regained and subsequently improve soil fertility, crop yield, food security, freshwater systems, etc. Finally, from the economic point of view, agricultural benefits possibly lead to farmers' economic stability and in combination with environmental goals, one more economic incentive is coming up to help farmers adopt carbon farming practices. Currently, there are several market products that can measure soil carbon or even provide platforms for issuing carbon credit certificates. A study performed by Cleantech Group in 2021 identified over 20 companies active in the following [99]:

- Sub-surface sampling
- Soil modelling
- Sub-surface sampling and soil modelling
- Surface sampling and soil modeling
- Soil analytics
- Satellite data.

Furthermore, a very small number of companies have been identified offering or advertising to offer in the medium-term future services relevant to issuing carbon credit certificates. In all cases, these companies follow a standard to measure SOC and then have an accreditation organism verify and certify the measurements. These certified measurements can then be utilized in schemes leading to the issue of carbon credit certificates. The average acre can generate about 0.2 credits annually, while at the same time in the US an income of 30 USD can be achieved per acre on an annual basis [100]. These figures highlight the dynamics of the market and the potential extra income for farmers especially taking into consideration the increasing perspective of carbon credit value. Many countries and unions around the world including the EU, Australia, and US are taking action with public policies in order to smooth the way for farmers entering the voluntary carbon market where they can sell the generated carbon credits to other entities that need them to balance their emissions [101]. For example, in Australia, the 2022 carbon farming projects reached 213 entries while in the period 2015–2021 there were 212 entries in total [100]. The private sector is already participating in such markets with one notable example being Microsoft that bought 40,000 credits from SOC sequestration generated through the Regen Network [102].

For these credits to correspond to real net reductions in GHGs and in order to be tradable, protocols have been developed. These protocols are in fact frameworks that define how to measure, monitor, report, and verify soil carbon sequestration (SOC MRV). Most of those focus on the benefits of GHG impacts of the project and each protocol has provisioned different included practices among cropping, tillage, grazing, input, and other variables that affect the state of the project. They refer to farming projects that implement conventional methods where they want to switch to regenerative agriculture practices. These protocols are designed to evaluate the impact of adopted practices in terms of the following:

- Additionality: The protocol evaluates whether the adopted practices in a project lead to emission reductions in addition to what would have happened by following conventional or other practices before project registration.
- Leakage: The protocol evaluates if project activities result in emission increase beyond project boundaries. For instance, if those activities for enhanced SOC sequestration lead to lower productivity, forcing agricultural land expansion in order to compensate, this will result in increased emissions in the net balance. Monitoring for potential losses is prescribed in all of the protocols.
- Reversal: There is a risk in the case of the release of SOC sequestered in previous observations, due to enforced actions or practices on the project. In order to mitigate this risk, a percentage of 5 or 10% of the credits goes to a buffer pool in most of the protocols.
- Permanence: Protocols require that generated carbon credits will remain in the soil in the long-term. Measures to mitigate the risk of reversals are in place. The permanence period can be 10, 20, 25, 30 years, equal to the credit generation period or dual options with 100 years period or 25 years with a 20% credit deduction, depending on the protocol.

A baseline scenario which refers to the initial SOC state of the project is being used to quantify the amount of generated carbon credits. Each protocol has differences, as shown above, with variations in the requirements between each MRV as described in [103]. The span of these variations is presented below:

- Measurement approach: One of the most popular approaches is sampling but models or remote sensing techniques are eligible in a few cases while hybrid approaches are also frequent.
- Model: In case of modeling approaches, DNDC, RothC, GGIT, FullCAM, or any other peer-reviewed model can be used.
- Baseline: With project registration a steady baseline can be set (static), a moving baseline depending on the results/predictions (dynamic), or both established by sampling.

- Stratification: In a few protocols there is required a minimum of 1–3 strata while in others it is at least recommended.
- Min samples: Three samples per strata or a number of required samples per 1000 ha.
- Sampling frequency: One sampling with project registration and least every 5 years after that.
- Allowable uncertainty: 10–20% in most cases.

From the public policy prism, the EU is positive to move forward with carbon farming [104] and seems to be in favor of carbon credits [105] but still, there is progress to be made at that level. Apart from legislation, there are also critical steps to be carried out [103]:

- Protocol differences and things to be changed especially in the capture of spatio-temporal variability. The prohibitive cost of sampling is an obstacle for capturing temporal variability and the requirements regarding the number of samples are simply also not enough to ensure accuracy in spatial variability of SOC. Sampling is crucial in order to establish a baseline and stratification, depending not on a standard number but on geographic and soil conditions, is important. Other means such as spectroscopy, remote sensing or hybrid methods must be explored.
- Credit equivalency issues that occur from inter-protocol requirements such as sampling depth and equivalent soil mass. All soil sampling protocols require taking samples at 30 cm, with recommendations reaching 1 or 2 m depth. Sampling depth is essential to understand the effect of the enforced practices on the SOC distribution as well as monitoring the changes in bulk density. Equivalent soil mass is taking into account the changes in bulk density that lead to different soil mass mainly in the topsoil and ultimately having more realistic measurements. A more unified approach among protocols regarding sampling will bring better credit equivalency. This step needs to be made in order to give the opportunity to farmers to trade their carbon credits, presenting them with another economic incentive to continue carbon farming practices and reduce permanence risk.
- Project scale issues that go hand in hand with uncertainty. In terms of sampling, smaller scale plots that meet the protocol requirements have denser samples than larger plots providing more certain measurements—which still may be not enough. On the other hand, with regard to modelling—that can be a valuable tool—uncertainty grows inversely related to field scale. Scale categories may not be possible to be set but generating credits depending on the uncertainty of the results is feasible. Finding the appropriate project scale will lead to more cost-efficient MRVs that will generate carbon credits with less risk in terms of additionality and reversal. Establishing a regional SOC sequestration overview in parallel with a project-scale overview will reduce risk of leakage.
- Benchmarking ability is the key in introducing new methods for measuring SOC sequestration and quantifying the uncertainty of the findings. A plethora of geographic conditions, soil structure, spectroscopy, and other data certainly exist in private or open-access libraries. The development of a joint open-access library of high standards will help shift the focus onto areas with a lack of data and eventually pave the way for better model calibration, a more accurate baseline, and higher determination.

Finally, Table 3 presents a summary of the literature review results performed in this section highlighting the key findings, gaps identified, and relevance.

Table 3. Summary of literature review findings of Section 5.

Reference	Key Findings	Gaps Identified	Relevance
[99]	Identified over 20 companies active in various aspects of soil carbon measurement and carbon credit certification, indicating a growing market.	Exploration of the long-term viability and scalability of these companies' technologies in different agricultural settings.	Demonstrates the market's response to carbon farming, aligning with the paper's focus on bridging research with practical applications.
[100]	Discusses the economic potential of carbon farming for farmers, including income generation from carbon credits.	Analysis of market barriers and incentives for widespread adoption of carbon farming practices.	Highlights the economic implications of carbon farming, relevant to policy development and market dynamics.
[101]	Details public policy actions supporting carbon farming, showing international movements towards integrating carbon farming into policy frameworks.	Assessment of the effectiveness of these policies in promoting sustainable farming and their impact on rural economies.	Provides context for the discussion on policy development and its influence on carbon farming practices and market dynamics.
[102]	Example of private sector engagement in carbon markets, with Microsoft's purchase of carbon credits, showcasing corporate interest.	Exploration of corporate motivations and the potential for long-term commitments to carbon farming projects.	Illustrates private sector involvement, underlining the importance of carbon farming in corporate sustainability strategies.
[103]	Discusses the protocol differences in soil-carbon measurement and credit issuance, highlighting the need for standardization.	Need for unified protocols to ensure accuracy, comparability, and trust in carbon credit markets.	Relevant to the paper's theme of integrating policy and technology for reliable carbon credit systems.
[104,105]	Indicate the EU positive stance towards advancing carbon farming, suggesting potential future developments in legislation and support.	Detailed analysis of how EU policies could evolve to support carbon farming initiatives more effectively.	Offers insight into the policy landscape, crucial for understanding the regulatory context of carbon farming in the EU.

6. Conclusions and Way Forward

Carbon farming is on the rise. Respective tools and tradable carbon credit certificates are nascent and need to scale up in order to meet the set goals. Research is showing that approaches encompassing different methods and technologies will be the way forward. Innovators need to combine different approaches and technologies in the most cost-effective way possible to support the uptake of these solutions especially by small and medium farmers. The technologies and approaches that can be combined can be summarized as given below:

- Satellite and drone multispectral photography.
- Eddy Covariance.
- Electro-conductivity either from ground sensors or non-contact sensors.
- Spectrometers, both portable and low-cost ground sensors since recently, spectral sensor breakouts became available for both visible and NIR with each having a cost of ~EUR 25.
- Farming and meteorological data analysis through farm management information systems (FMIS).

All the above will essentially be combined through the use of AI and Big Data analytics technologies, as presented graphically in Figure 2.

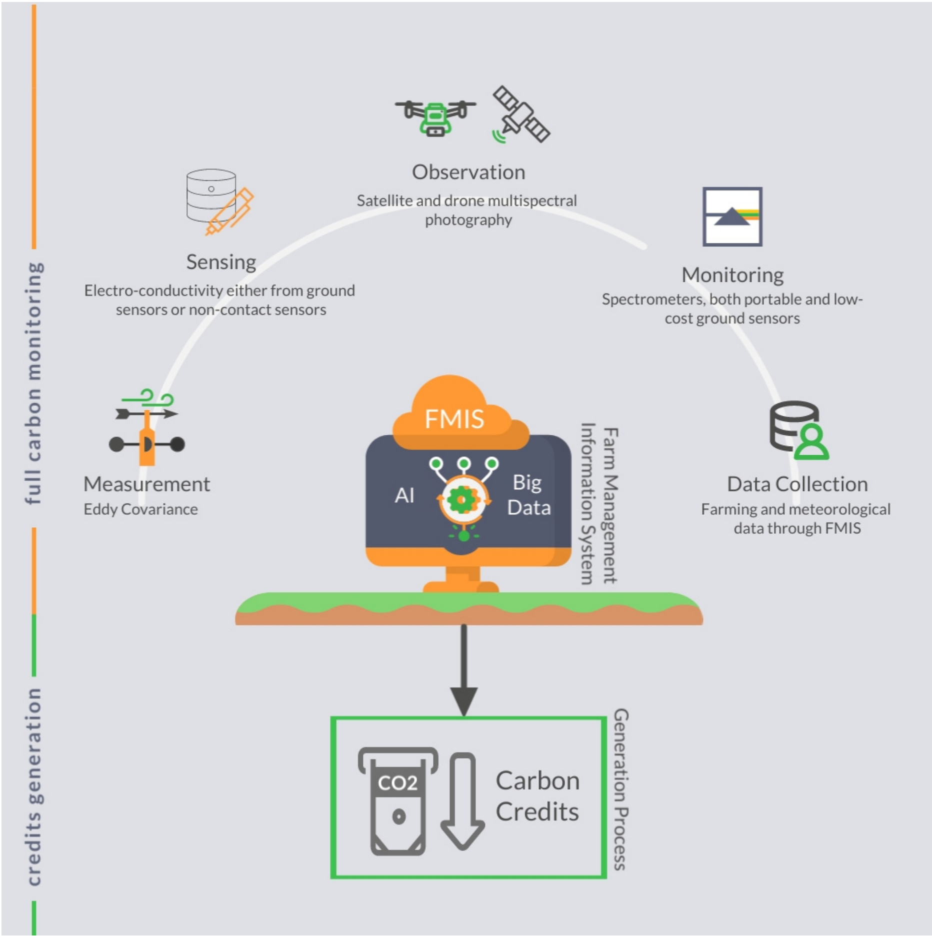

Figure 2. Technology paving the road towards issuing tradable carbon credit certificates.

Future possible research paths stemming from the results of this research include the following:

- Carbon farming policy impact and adaptation studies.
- Long-term sustainability and economic analysis of carbon farming.
- Integration of AI, remote sensing, and IoT in achieving lower cost, accurate carbon stock estimations at farm level.
- Investigation of carbon credit market dynamics and evaluation of possible farmer incentives.
- Investigation of the interaction of carbon farming with ecosystem services and biodiversity.
- Scalability and barriers to adoption of carbon farming technologies.
- Determination of the impact of carbon farming on the technical progress of agriculture.

The ultimate outcome will be easy access for farmers to issue tradable carbon credit certificates, increasing their income while providing an invaluable service to removing and storing atmospheric CO_2.

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