AI-Assisted Precision Carbon Farming for Sustainable Agroecosystem Management and Greenhouse Gas Mitigation: A Synthesis of Current Evidence and Emerging Frameworks

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Received: 27 May 2026
Revised: 09 Jun 2026
Accepted: 28 Jun 2026
Published: 18 Jul 2026

E-ISSN: 2989-5340
DOI: https://doi.org/10.54660/jafi.2026.6.2.33-40

ABSTRACT

Agriculture and the agrifood domain are major anthropogenic sources of GHG emissions, but agriculture can also help climate mitigation, as it can provide significant opportunities for SOC sequestering. Artificial intelligence in this regard, along with geospatial technologies, IoAT and digital twins, is increasingly regarded as a technological foundation of carbon-smart farming which aims to marry productivity, economic benefits, and carbon management.

This review aims to summarize the existing information published mostly between 2019 and 2026 regarding AI-enabled carbon-smart farming, so as to consolidate the existing proof on the use of ML, DL, remote sensing, GIS, IoAT and digital twins' technologies in carbon monitoring, GHG emissions reduction and agroecosystems climate friendly management.

Framework: The reviewed works are grouped into four connected themes: (i) AI-driven predictive modelling of SOC and GHG emissions; (ii) carbon measurement through remote sensing and GIS; (iii) IoAT and digital twin systems for real-time field monitoring; and (iv) carbon accounting, measurements, reporting and verification that convert modelling and monitoring findings into verifiable carbon credits.

General findings: The materials reviewed testify to the fact that tree-based ensemble algorithms (random forest, gradient boosting, XGBoost) as well as deep neural architectures are mostly used for SOC and GHG emissions modelling (the coefficients of determination of the developed models often exceed 0.80 thanks to the application of remote sensing, radar and soil proximal sensing methods). Digital twin and IoAT systems are still being introduced and face lots of obstacles due to variability of data, cost of sensors and challenges related to interoperability. Moreover, MRV procedures have some inconsistencies in their methodology in terms of sampling depth and accounting method, which does not allow for adequate comparison of carbon credits from different programmes. The majority of studies highlight regenerative techniques (like conservation tillage, cover cropping and crop rotation) used for optimisation of the process in both spatial and temporal terms.

Scientific significance and conclusion the convergence of AI, geospatial monitoring and carbon accounting infrastructure represents a scientifically credible pathway toward scalable and verifiable soil carbon sequestration, but the literature consistently identifies data standardisation, model transferability across agroecological zones, and transparent MRV governance as prerequisites for translating research advances into climate-neutral agricultural systems at scale.

Keywords: Digital agroecosystem monitoring; machine learning for soil carbon; geospatial carbon accounting; smart sensing networks; climate-resilient land management; agricultural greenhouse gas modelling; verified carbon credit systems; data-driven regenerative management

1. Introduction

1.1. Global climate change, agriculture and the carbon farming concept

Adding up total emissions from agricultural production right up to the land use, as well as pre-production and post-production emissions – agriculture is responsible for around one-third of total anthropogenic emissions (Food and Agriculture Organization of the United Nations, 2025) [1]. More than fifty percent of these emissions come from the process of crop and livestock production known as farm-gate emissions (Food and Agriculture Organization of the United Nations, 2025) [1]. Even if it is true that the emissions per unit of production decreased, the total agricultural emissions amount continued to rise. This shows that the share of agriculture in the total emissions decreased alongside the increasing share of emissions from the energy-industrial complex as well (Food and Agriculture Organization of the United Nations, 2020) [2] (Tubiello *et al.*, 2022) [35]. The report issued by IPCC assigned agriculture to the category of sectors providing for the opportunities for getting net-negative emissions due to carbon sequestration through soils and bio-mass, making the issue of carbon farming relevant as one of the key aspects of the mitigation strategy (Intergovernmental Panel on Climate Change, 2022) [3].

Soil holds the largest land-based stock of organic carbon available for management purposes, and restoring compromised agricultural soils back to their potential for sequestering carbon has been seen as potential means for implementation of mitigation with the co-benefits of fertility, water retention and robustness (Lal, 2004) [4] (Paustian *et al.*, 2016) [5]. The global initiative "4 per 1000" is an example of how ambitious soil carbon sequestration might be, suggesting that even small annual growth rates of carbon reserves in soils worldwide could enable offsetting a significant share of emissions from human activities (Minasny *et* *al*., 2017) [6]. However, many subsequent studies indicate that achieving such rates in practice may not be possible due to limitations of soil and climate conditions (Minasny *et al*., 2017) [6]. Therefore, the term of "climate-smart soil management" has been coined as a joint application of soil science, agronomy and remote monitoring of soils to achieve goals of productivity, adaptation and mitigation.

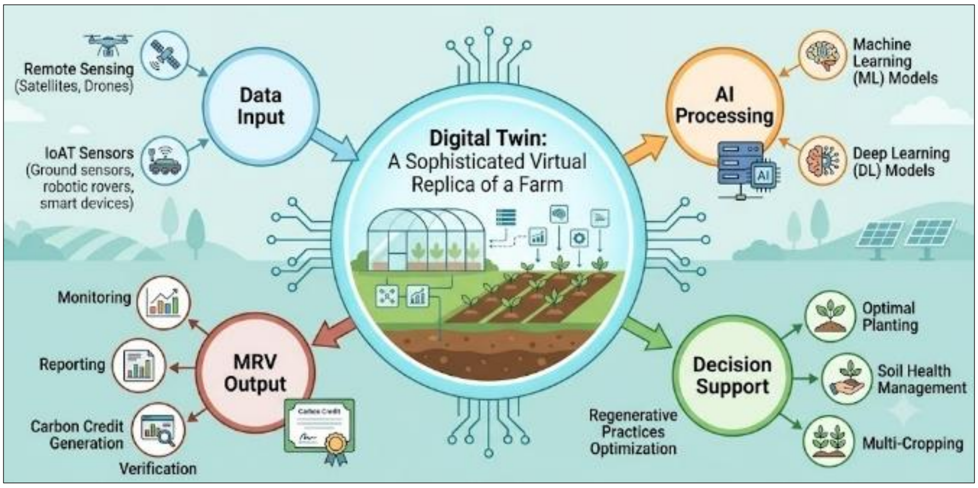

Fig 1: AI-Driven Precision Carbon Farming Framework

1.2. Artificial intelligence in precision agriculture and digital carbon monitoring

Precision agriculture has progressed from basic variable-rate application to data-based AI systems that integrate data from multiple sources such as sensors and weather (Wolfert *et al*., 2017) [21]. Machine learning techniques like random forests, gradient-boosted trees, support vector machines, convolutional neural networks, and recurrent models like long-short-term memory networks are being widely used to predict yield, nutrient content, and even carbon and GHG emissions (Kamilaris and Prenafeta-Boldú, 2018) [22] (Chlingaryan *et al*., 2018) [23] (van Klompenburg *et al*., 2020) [24]. A thorough analysis of AI applications in soil organic carbon measurement shows that ensemble tree algorithms and more recently hybrid AI-biogeochemical models dominate the literature and have better results than pure mechanistic or statistical models whenever sufficient data for training is available (Ding *et al*., 2025) [8]. AI is also used to improve location selection, injection process optimization, and leak detection in engineered carbon capture and storage processes and environments, shifting its role from ecological evaluation to operational decision making.

In addition to prediction, there are also new attempts to use multi-agent systems based on large language models for hypothesis generation tasks in soil carbon studies, showing another, still not defined, but promising use of AI in accelerating scientific discoveries.

1.3. Remote sensing, GIS and geospatial carbon assessment

AI-assisted SOC and mapping vegetation condition heavily depend on data provided by remote-sensing satellites (Sentinel-2 with its multispectral capability and Sentinel-1 equipped with synthetic aperture radar) and UAVs with sensors operating along a range of spectrums from multi- to hyperspectral perspectives and thermal data (Crucil *et al*., 2019) [16] (Heil *et al*., 2022) [17] (Datta *et al*., 2022) [18]. Data-based vegetation indices (such as Normalized Difference Vegetation Index and several other red-edge-based ones) can help determine the nitrogen status of the canopy that correlates with residues and biomass (in terms of how they affect soil carbon dynamics) (Crucil *et al*., 2019) [16]. These innovations have helped narrow down the technology gaps between satellite and land-level precision agriculture remote sensing. Although it is true that satellite imagery is still a moderately low-resolution product.

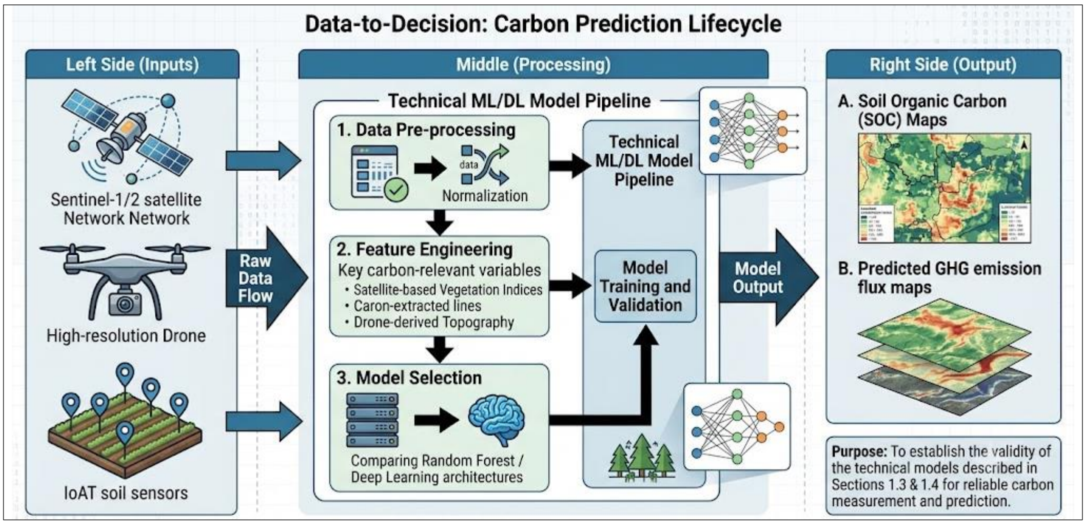

Fig 2: The Data-to-Decision Pipeline (Machine Learning Workflow)

1.4. Digital twins, the Internet of Agricultural Things and regenerative agriculture

Digital twin technology which continually replicates a physical farm and is powered by sensor data has been recognized as a tool that can link IoAT sensor networks, predictive models based on artificial intelligence, and geospatial data into a single decision-support system (Verdouw *et al*., 2021) [10] (Pylianidis *et al*., 2021) [11]. Systematic reviews show that while the idea of digital twins has found applications in manufacturing and urban agriculture, their practical usage in agriculture is still limited, primarily due to the nature of agricultural systems that are much more complex than industrial systems (Jones *et al*., 2020) [13] (Barricelli *et al*., 2019) [14]. The Internet of Agricultural Things expands traditional IoT systems to include sensor networks that monitor soil, weather, and greenhouse gases and poses certain challenges to field deployment, mainly in terms of powering devices and using edge computing technologies (Liu *et al*., 2022) [15].

This agriculture method includes no tillage or reduced tillage, use of cover crops, crop diversification and utilizing organic nutrients in the soil. Regenerative agriculture is considered to be an important method used in carbon farming, which has both benefits of improving the soil but also supporting biodiversity and helping with water infiltration (LaCanne and Lundgren, 2018) [32] (Giller *et al*., 2021) [33]. Despite being helpful, it must be noted that research in the field shows lack of empirical evidence showing the difference in soil carbon accumulation process between regenerative and conventional approaches (LaCanne and Lundgren, 2018) [32] (Giller *et al*., 2021) [33].

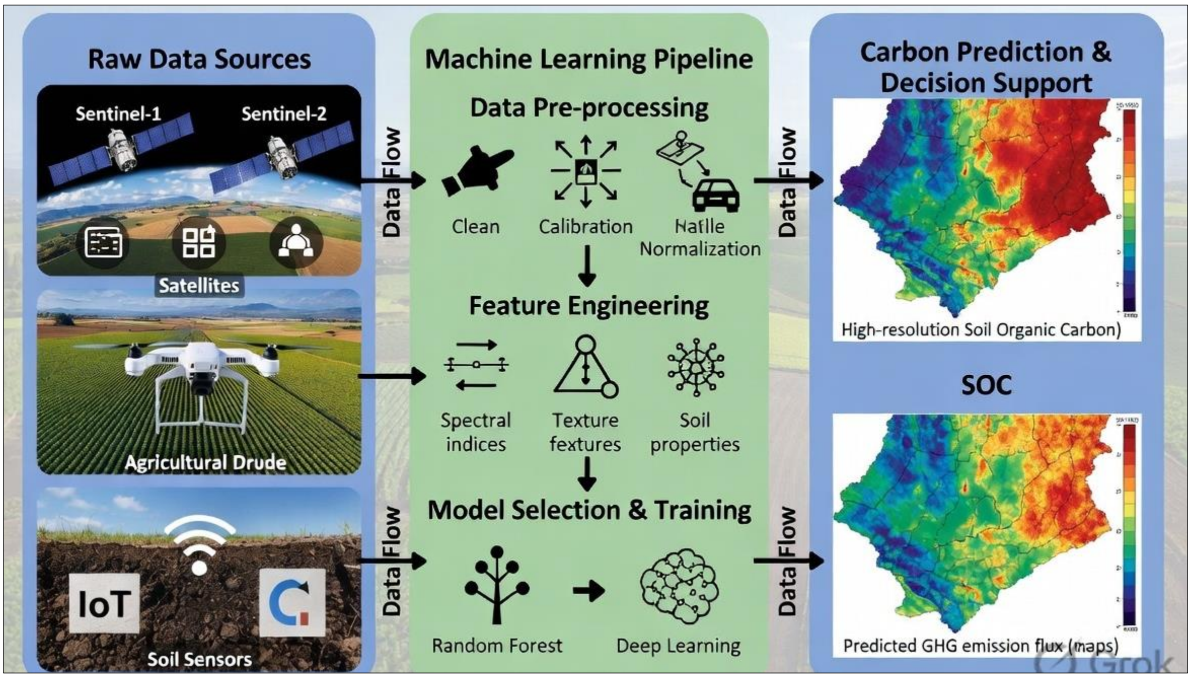

Fig 3: Digital Twin & IoAT Architecture for Field Monitoring

1.5 Carbon accounting and measurement, reporting and verification (MRV)

Since SOC changes generally tend to be minor compared to background stocks and heterogeneous, credible MRV is the key limitation in scaling up agricultural carbon markets (Smith *et al*., 2020) [19]. MRV protocols available in public domain were reviewed and serious discrepancies in the method of accounting (fixed depth vs equivalent soil mass) and in the sampling depth methods were found; 13 out of 24 reviewed approaches were based on shallow sampling (0–30 cm), although research shows that the greater share of SOC stock and the signal change takes place at the greater depth (Smith *et al*., 2020) [19]. At that, practical MRV approaches implemented on a large scale confirm that with the help of the hybrid soils sampling approach and biogeochemical modeling verified emission reductions can be obtained on hundreds of thousands of hectares while showing at the same time how sensitive the results obtained due to the net accounting system to the deductions for uncertainty and variability of practices, especially in case of tillage intensity change (Brummitt *et al*., 2024) [31]. The results obtained provide support to the general calls of the research community for the need in standard, science-based MRV governing so that credited SOC sequestered is additional and durable climate benefit instead of methodological bias (Oldfield *et al*., 2022) [29].

1.6. Research gaps and objectives of the present review

Though individual literatures on the use of AI in SOC prediction, remote sensing, IoAT, digital twins and carbon MRV have been growing rapidly, not many studies combine these fields into a single thorough representation of AI-assisted carbon precision farming as a practical agroecosystem management concept. Other unresolved issues include model transferability across both agroecological zones and soil types; the compatibility of different sensor and image data streams; practical readiness of digital twins at the level of a farm; harmonizing MRVs in voluntary carbon markets. The purpose of this review is therefore to review relevant literature across those four issues: (i) define the main AI, geospatial and IoAT methods used for precision carbon farming; (ii) summarize the currently available information on soil carbon, greenhouse gas emission and agroecosystem benefits from such methods; (iii) critically assess methodological limitations and challenges outlined in the literature; and (iv) formulate research priorities regarding AI-assisted agroecosystem management.

2. Conceptual Framework and Methodological Approach

This article is structured as a narrative-synthesis review rather than a primary field experiment. The methodological description below therefore characterises, at a conceptual level, the classes of technology and analytical approach reported across the reviewed literature, consistent with how such systems are described and implemented in published AI-assisted precision carbon farming studies. No original experimental data, proprietary algorithms, source code or computational pipelines are presented; the intent is to synthesise published evidence into a coherent conceptual framework suitable for guiding future primary research and journal-formatting practice.

2.1. AI-assisted predictive and decision-support framework

Across the reviewed literature, AI-assisted carbon farming frameworks typically combine (i) supervised ML/DL models trained to predict SOC stocks, sequestration rate, or GHG flux from remotely sensed, proximally sensed and climatic covariates; (ii) decision-support layers that translate model outputs into spatially differentiated management recommendations (e.g., variable-rate amendment or residue management); and (iii) digital-twin or dashboard interfaces that present integrated model, sensor and geospatial outputs to farm managers and agronomists (Ding *et al*., 2025) [8] (Verdouw *et al*., 2021) [10] (Ghandar *et al*., 2021) [12]. Reported algorithm families include random forest, gradient boosting/XGBoost, support vector regression, partial least squares regression, artificial neural networks and convolutional or recurrent deep-learning architectures, often applied in ensemble or hybrid combination with process-based biogeochemical models such as DNDC or DayCent for cross-validation (Ding *et al*., 2025) [8] (Saha *et al*., 2021) [28].

2.2. Remote sensing and GIS-based geospatial assessment

Geospatial assessment pipelines described in the literature typically integrate multispectral and radar satellite imagery (e.g., Sentinel-1/2), UAV-based multispectral, hyperspectral and thermal imagery, and ancillary GIS layers such as digital elevation models, soil maps and land-cover classifications, from which vegetation and soil-moisture indices are derived as predictor variables for spatial SOC and carbon-hotspot mapping (Crucil *et al*., 2019) [16] (Heil *et al*., 2022) [17] (Datta *et al*., 2022) [18] (Mulla, 2013) [36].

2.3. IoAT, smart sensing and digital-twin integration

IoAT architectures reported in the literature typically comprise soil moisture, temperature and (less commonly) direct SOC or greenhouse-gas sensors, automated weather stations, and wireless communication networks feeding edge- and cloud-based data platforms, which in more advanced implementations are coupled to a digital-twin layer for real-time simulation and scenario testing (Verdouw *et al*., 2021) [10] (Pylianidis *et al*., 2021) [11] (Liu *et al*., 2022) [15]. Reviews of digital-twin adoption emphasise that, while conceptual architectures are well described, full closed-loop integration of sensing, modelling and automated actuation at field scale remains comparatively rare in the published literature relative to laboratory, greenhouse or urban-agriculture case studies (Jones *et al*., 2020) [13] (Barricelli *et al*., 2019) [14].

2.4. Carbon accounting and MRV synthesis approach

The MRV dimension of this review synthesises published protocol comparisons and operational case studies, focusing on reported accounting methods, sampling-depth requirements, uncertainty treatment and the role of AI/geospatial data in reducing measurement cost and improving spatial representativeness of soil carbon credit claims (Smith *et al*., 2020) [19] (Brummitt *et al*., 2024) [31] (Oldfield *et al*., 2022) [29].

3. Synthesis of Evidence from the Literature

3.1. Performance of AI models in soil organic carbon and GHG prediction

Reported predictive performance varies with covariate richness and study scale, but ensemble tree-based methods recur as top performers across the reviewed studies. Gradient boosting and random forest algorithms combining soil-moisture, spectral and topographic covariates are consistently reported among the strongest performers for soil carbon and related soil-process prediction tasks, outperforming single-algorithm baselines through their capacity to represent nonlinear ecological interactions (Ding *et al*., 2025) [8].

Sentinel-1/2 fusion approaches that combine multispectral vegetation and moisture indices with radar-derived texture metrics, evaluated using XGBoost, random forest and support vector machine regressors, have been reported to improve spatial SOC prediction accuracy relative to optical-only models, particularly in conservation-agriculture systems where residue cover complicates optical signal interpretation (Crucil *et al*., 2019) [16] (Datta *et al*., 2022) [18].

For direct greenhouse-gas flux prediction, machine learning models trained on management, soil and weather covariates have been shown to improve prediction of nitrous oxide emissions from intensively managed cropping systems relative to conventional emission-factor approaches, supporting more spatially and temporally resolved emissions accounting than static IPCC Tier 1 coefficients (Saha *et al*., 2021) [28] (Zhang *et al*., 2015) [34].

3.2. Spatial carbon distribution and remote sensing evidence

GIS-based spatial synthesis of SOC and vegetation-index data consistently reveals substantial within-field and within-landscape heterogeneity in carbon status, correlated with topographic position, historical land use and cropping intensity, underscoring the rationale for management-zone delineation rather than uniform, field-average treatment (Crucil *et al*., 2019) [16] (Heil *et al*., 2022) [17] (Mulla, 2013) [36]. UAV-based fine-scale mapping studies report that drone-derived multispectral and hyperspectral imagery can resolve SOC and soil organic matter variability at sub-field resolutions unattainable with moderate-resolution satellite products alone, although at higher per-hectare data-acquisition cost (Heil *et al*., 2022) [17].

3.3. Greenhouse gas emissions and mitigation efficiency

Precision agriculture technologies, including variable-rate fertilisation, controlled-traffic farming and precision irrigation, are reported across multiple reviews to contribute positively to GHG mitigation by reducing nitrogen surplus and associated nitrous oxide emissions, and by improving fuel- and water-use efficiency relative to uniform management (Balafoutis *et al*., 2017) [27]. At the systems level, FAO accounting indicates that livestock enteric fermentation and manure management, together with synthetic nitrogen fertiliser application, remain the dominant single sources of farm-gate non-CO2 GHG emissions, framing nitrogen-use efficiency and livestock management as priority targets for AI-assisted mitigation interventions (Food and Agriculture Organization of the United Nations, 2025) [1]

(Zhang *et al*., 2015) [34]. Machine-learning-based emission prediction is reported to support more granular identification of emission hotspots than static national inventory methods, potentially enabling targeted mitigation prioritisation within heterogeneous farm landscapes (Saha *et al*., 2021) [28].

3.4. Agroecosystem performance, regenerative practice adoption and sustainability outcomes

Long-term comparative studies of regenerative cropping systems report positive effects on soil health and in-field biodiversity indicators relative to conventional management, alongside evidence that ecosystem-service delivery from soil biogeochemical processes is generally enhanced under regenerative organic management, although yield outcomes relative to conventional systems remain more variable and context-dependent (LaCanne and Lundgren, 2018) [32] (Giller *et al*., 2021) [33]. Climate-smart agricultural practices more broadly are associated in a comprehensive multi-decade review with improvements in productivity, income, resource-use efficiency and climate resilience, alongside GHG mitigation, indicating that carbon-focused management need not trade off against farm profitability when practices are well matched to local agroecological conditions.

3.5. Carbon accounting, credit generation and economic considerations

Operational MRV pipelines deployed across large enrolled-farmer networks demonstrate that hybrid modelling and stratified soil sampling can generate verified emission reductions at scales of hundreds of thousands of hectares, with cover-crop introduction showing the most consistent emission-reduction signal across enrolled fields, while tillage-intensity reduction shows more spatially and temporally variable impact (Brummitt *et al*., 2024) [31]. Comparative reviews of MRV protocols nonetheless caution that inconsistent accounting method and sampling-depth requirements across voluntary carbon-market programmes introduce material uncertainty into credited carbon volumes, a methodological weakness that AI-assisted, spatially explicit monitoring is proposed, but not yet consistently demonstrated at scale, to help resolve (Smith *et al*., 2020) [19] (Oldfield *et al*., 2022) [29].

4. Literature-Based Summary Tables

The following tables synthesise reported information from the reviewed literature and are not primary experimental data; each row is traceable to the numbered reference(s) indicated.

Table 1: Global agricultural greenhouse gas emissions: scale and composition reported in the literature.

Indicator	Reported value / trend	Source
Total agrifood system emissions (2023)	~16.5 Gt CO2eq; ~one-third of global anthropogenic GHG emissions	[1]
Farm-gate crop and livestock emissions (2023)	8.1 Gt CO2eq (49% of agrifood emissions)	[1]
Land-use change emissions	3.2 Gt CO2eq (19% of agrifood emissions)	[1]
Agriculture share of global GHG emissions, 1990s vs. 2010s	Declined from ~29% to ~20% of total economy-wide emissions	[2]
Livestock enteric fermentation share of agricultural GHG	~20-26% of agricultural GHG emissions	[34]
Emissions intensity of agricultural production (2023 vs 2001)	1.9 kg CO2eq per international dollar; down 25% since 2001	[1]

Table 2: AI/ML and deep-learning algorithm families reported for soil carbon and greenhouse-gas prediction.

Algorithm family	Typical application reported	Representative source(s)
Random forest / gradient boosting (incl. XGBoost)	SOC spatial prediction; N2O flux prediction; dominant environmental-control identification	[8], [16], [28]
Support vector machine / regression (SVM/SVR)	SOC and soil-nutrient prediction from spectral covariates	[8], [16]
Partial least squares regression (PLSR)	Hyperspectral SOC/soil organic matter calibration	[8], [18]
Artificial neural networks (ANN)	Nonlinear SOC and yield prediction	[8], [24]
Convolutional / recurrent deep networks (CNN, LSTM)	Image-based crop and soil feature extraction; time-series yield and emissions forecasting	[22], [24], [25]
Hybrid AI-biogeochemical models	Cross-validation of AI predictions against process-based models (e.g., DNDC, DayCent)	[8], [28]

Table 3: Remote sensing and UAV platforms reported for carbon and vegetation monitoring.

Platform / sensor type	Data contribution	Representative source(s)
Sentinel-2 multispectral imagery	Vegetation indices (NDVI, NDRE); land cover; biomass proxies	[16], [36]
Sentinel-1 synthetic aperture radar	Soil moisture and surface roughness; residue/texture information	[16]
UAV multispectral sensors	Fine-scale SOC and soil organic matter mapping; nutrient-stress indices	[17], [18]
UAV hyperspectral sensors	High-resolution SOC and soil property calibration	[16], [18]
UAV thermal imagery	Canopy temperature; water-stress and evapotranspiration estimation	[36]

Table 4: IoAT and digital-twin infrastructure components reported in the literature.

Component	Reported function	Representative source(s)
Soil moisture / temperature sensors	Continuous edaphic monitoring feeding ML/digital-twin models	[10], [15]
Weather stations	Local meteorological input for crop and emissions models	[10], [21]
Wireless sensor networks / low-power communication	Field-scale data transmission; energy-constrained deployment	[15]
Edge and cloud computing	Local pre-processing and centralised model synchronisation	[11], [14]
Digital-twin dashboard / simulation layer	Real-time visualisation and scenario testing for management decisions	[10], [11], [12], [13]

Table 5: Carbon accounting and MRV protocol features reported in the literature.

MRV element	Reported practice / issue	Representative source(s)
Accounting method	Fixed-depth vs. equivalent-soil-mass; inconsistent across protocols	[19]
Sampling depth	Most protocols specify 0-30 cm despite deeper SOC stock relevance	[19]
Modelling approach	Hybrid empirical sampling + biogeochemical modelling (e.g., DNDC, DayCent)	[19], [31]
Scale of deployment demonstrated	Verified reductions reported across >500,000 ha in one operational pipeline	[31]
Uncertainty and leakage treatment	Deductions applied for uncertainty and potential leakage before crediting	[31]
Credibility / additionality concerns	Comparability of credits questioned across differing protocols	[19], [29]

Table 6: Comparative synthesis of reviewed technology domains and reported outcomes.

Technology domain	Reported maturity	Principal reported benefit	Principal reported constraint
AI-based SOC/GHG prediction	Moderate-high; extensive literature since 2019	Improved spatial and temporal resolution of carbon/emissions estimates	Model transferability across soils and agroecological zones
Remote sensing / GIS	High; well-established	Cost-effective, scalable spatial coverage	Moderate-resolution products limit fine-scale detection
IoAT sensing networks	Early-moderate	Continuous, high-frequency field data	Sensor cost, power supply, data heterogeneity
Digital twins	Early	Integrated real-time decision support	Limited farm-scale, closed-loop deployment evidence
Carbon accounting / MRV	Moderate; rapidly evolving	Enables monetisation of verified sequestration	Protocol inconsistency undermines credit comparability

5. Discussion

5.1 AI-assisted carbon farming in the context of precision and digital agriculture

The reviewed evidence positions AI-assisted precision carbon farming as a natural extension of the broader digital-agriculture trajectory described since the mid-2010s, in which big-data analytics and, subsequently, deep learning was progressively integrated into farm decision-making (Wolfert *et al*., 2017) [21] (Kamilaris and Prenafeta-Boldú, 2018) [22]. Framed as the design of sustainable agricultural systems through digital technology, this trajectory extends naturally to carbon management, where the object of optimisation shifts from short-term yield toward longer-term, spatially distributed carbon stock change (Basso and Antle, 2020) [20]. This reframing is consistent with the recurring observation across the reviewed studies that the same core AI toolkit, ensemble tree-based learners and, increasingly, deep architectures, is being redeployed from yield and nutrient-status prediction toward SOC and GHG-flux prediction, suggesting methodological convergence rather than the emergence of an entirely distinct technical discipline (Chlingaryan *et al*., 2018) [23] (van Klompenburg *et al*., 2020) [24].

5.2. Consistency and divergence with prior international studies

The finding that ensemble and hybrid AI-biogeochemical models outperform single-algorithm or purely mechanistic approaches for SOC prediction is broadly consistent across the reviewed sources, lending reasonable confidence to this conclusion despite differing study regions and covariate sets (Ding *et al*., 2025) [8]. There is less consensus, however, regarding the practical readiness of digital-twin architectures: while conceptual and case-study literature (e.g., aquaponic and greenhouse applications) demonstrates technical feasibility, systematic reviews of farm-scale deployment consistently describe the field as being at an early, pre-commercial stage, in contrast to the more mature remote-sensing and IoAT sensing literatures (Jones *et al*., 2020) [13] (Barricelli *et al*., 2019) [14]. Similarly, while climate-smart and regenerative agricultural practices are widely reported to deliver co-benefits for productivity, resilience and GHG mitigation, the magnitude of reported soil carbon and yield responses varies considerably by agroecological context, cautioning against extrapolating results from any single regional study to global recommendations.

5.3. Practical implementation challenges

Several cross-cutting implementation challenges recur across the reviewed literature. First, data interoperability: heterogeneous sensor formats, imagery resolutions and reporting standards complicate the integration of IoAT, remote sensing and laboratory soil data into unified AI pipelines. Second, model transferability: models trained in one agroecological zone or soil type frequently show degraded performance when applied elsewhere, limiting the direct generalisation of published accuracy metrics. Third, infrastructure cost and connectivity: dense IoAT sensor networks and continuous UAV monitoring remain economically challenging for smallholder systems, concentrating documented deployments in well-resourced research or commercial contexts. Fourth, MRV governance: the absence of harmonised accounting and sampling standards across voluntary carbon-market protocols introduces uncertainty that AI and remote sensing can help characterise but cannot, on their own, resolve without accompanying institutional standardisation.

5.4. Economic feasibility

Economic feasibility in the reviewed literature is discussed primarily through two lenses: input-use efficiency gains from precision management, and carbon-credit revenue from verified sequestration. Precision agriculture technologies are reported to contribute positively to both farm economics and GHG mitigation simultaneously, suggesting that efficiency-oriented adoption pathways need not be contingent on carbon-market participation (Balafoutis *et al*., 2017) [27]. Carbon-credit-oriented pathways, by contrast, remain more sensitive to MRV cost and uncertainty deductions, and the scientific literature is cautious about overstating near-term monetisation potential given the persistent methodological inconsistencies identified in Section 3.5 (Smith *et al*., 2020) [19] (Oldfield *et al*., 2022) [29].

5.5. Study limitations

As a narrative synthesis rather than a systematic review with pre-registered protocol or meta-analytic pooling, this article does not exhaustively capture every published study within its scope, and the reference set, while spanning the principal technology domains, is illustrative rather than comprehensive. No original field trial, model training, or primary quantitative analysis was undertaken; all quantitative figures reported here are drawn from, and attributed to, the cited literature. Because the underlying literature itself is methodologically heterogeneous (in study region, soil type, algorithm choice and validation procedure), direct numerical comparison across cited studies should be treated as indicative rather than statistically pooled evidence.

5.6. Future research opportunities

Priority research directions identified across the reviewed literature include: (i) multi-site, multi-year benchmarking of AI models for SOC and GHG prediction to establish transferability limits across soils and climates; (ii) open, interoperable data standards for IoAT and remote-sensing data streams to lower integration barriers; (iii) longitudinal, field-scale digital-twin case studies extending beyond controlled or urban-agriculture settings; (iv) harmonisation of MRV accounting method and sampling-depth requirements across voluntary carbon-market protocols; and (v) explicit integration of socioeconomic and smallholder-accessibility considerations into the design of AI-assisted carbon farming systems, so that technological advances translate into equitable as well as scientifically credible mitigation outcomes.

6. Conclusion

This literature review presents a synthesis of current evidence on AI-enhanced carbon farming practices in the context of four interconnected fields; i.e., the prediction of soil carbon and greenhouse gas dynamics with the use of AI, GIS and remote sensing methods, IoT and digital twin physical infrastructure, as well as carbon accounting and monitoring. In particular, the literature consistently reports that ensemble and hybrid machine learning techniques, in conjunction with different soil sensing data (multispectral, radar, and proximal), yield the most significant improvement in soil carbon and GHGs prediction accuracy. At the same time, regenerative agricultural practices like reduced tillage, cover cropping or diversified rotation remain the most important management practices complemented by using those AI technologies for its spatial targeting.

The theoretical contribution of the literature synthesis is that it confirms the individuality of that technologies used in AI-enabled precision carbon farming. However, the gap between technology maturity and actual adoption of AI for the clear farming practice still exists. In practice, the review highlights that AI can provide immediate value with respect to improvement of input use efficiency and targeting of regenerative practices, while the mechanized earning of carbon credits will depend on solving existing

The priorities of the researchers involve the benchmarking of multi-region models and the establishment of open data standards, while the priorities for the policymakers are aligned with the harmonization of MRV protocols and funding the IoAT infrastructure, especially for the smallholder systems. From the point of view of farmers and agronomists, their priorities lie in the gradual introduction of AI-based decision support technology, starting from the implementation of input efficiency applications in order to achieve profit independently of climate market mechanisms. Advanced technologies like AI, digital twins, geospatial monitoring and carbon accounting systems, developed together, will help, or at least contribute to the introduction of a scientifically proven technology allowing carbon sequestration in the soil.

References

1. Food and Agriculture Organization of the United Nations. Greenhouse Gas Emissions from Agrifood Systems: Global, Regional and Country Trends, 2001–2023. FAOSTAT Analytical Brief. Rome: FAO; 2025. p. 1-24.
2. Food and Agriculture Organization of the United Nations. The Share of Agriculture in Total Greenhouse Gas Emissions: Global, Regional and Country Trends 1990–2017. FAOSTAT Analytical Brief. Rome: FAO; 2020. p. 1-16.
3. Intergovernmental Panel on Climate Change. Climate Change 2022: Mitigation of Climate Change. Working Group III Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Geneva: IPCC; 2022. p. 1-2913.

4. Lal R. Soil carbon sequestration to mitigate climate change. Geoderma. 2004;123(1-2):1-22.
5. Paustian K, Lehmann J, Ogle S, Reay D, Robertson GP, Smith P. Climate-smart soils. Nature. 2016;532(7597):49-57.
6. Minasny B, Malone BP, McBratney AB, Angers DA, Arrouays D, Chambers A, *et al*. Soil carbon 4 per mille. Geoderma. 2017;292:59-86.
7. Lal R. Artificial intelligence for assessing organic matter content and related soil properties. Journal of Soil and Water Conservation. 2024;79(6):171A-180A.
8. Ding J, Padarian J, Minasny B, McBratney AB. Advancing soil organic carbon prediction: a comprehensive review of technologies, AI, process-based and hybrid modelling approaches. Advanced Science. 2025;12(8):2405123.
9. Minasny B, Chen S, McBratney AB. AI as a catalyst for cross-disciplinary breakthroughs in soil carbon sequestration research. European Journal of Soil Science. 2025;76(4):e70012.
10. Verdouw C, Tekinerdogan B, Beulens A, Wolfert S. Digital twins in smart farming. Agricultural Systems. 2021;189:103046.
11. Pylianidis C, Osinga S, Athanasiadis IN. Introducing digital twins to agriculture. Computers and Electronics in Agriculture. 2021;184:105942.
12. Ghandar A, Ahmed A, Zulfiqar S, Hua Z, Hanai M, Theodoropoulos G. A decision support system for urban agriculture using digital twin: a case study with aquaponics. IEEE Access. 2021;9:35691-35708.
13. Jones D, Snider C, Nassehi A, Yon J, Hicks B. Characterising the digital twin: a systematic literature review. CIRP Journal of Manufacturing Science and Technology. 2020;29:36-52.
14. Barricelli BR, Casiraghi E, Fogli D. A survey on digital twin: definitions, characteristics, applications, and design implications. IEEE Access. 2019;7:167653-167671.
15. Liu Y, Li D, Du B, Shu L, Han G. Rethinking sustainable sensing in agricultural internet of things: from power supply perspective. IEEE Wireless Communications. 2022;29(4):102-109.
16. Crucil G, Castaldi F, Aldana-Jague E, van Wesemael B, Macdonald A, Van Oost K. Assessing the performance of UAS-compatible multispectral and hyperspectral sensors for soil organic carbon prediction. Sustainability. 2019;11(7):1889.
17. Heil J, Jörges C, Stumpe B. Fine-scale mapping of soil organic matter in agricultural soils using UAVs and machine learning. Remote Sensing. 2022;14(14):3349.
18. Datta D, Paul M, Murshed M, Teng SW, Schmidtke L. Soil moisture, organic carbon, and nitrogen content prediction with hyperspectral data using regression models. Sensors. 2022;22(20):7998.
19. Smith P, Soussana JF, Angers D, Schipper L, Chenu C, Rasse DP, *et al*. How to measure, report and verify soil carbon change to realize the potential of soil carbon sequestration for atmospheric greenhouse gas removal. Global Change Biology. 2020;26(1):219-241.
20. Basso B, Antle J. Digital agriculture to design sustainable agricultural systems. Nature Sustainability. 2020;3(4):254-256.
21. Wolfert S, Ge L, Verdouw C, Bogaardt MJ. Big data in smart farming: a review. Agricultural Systems. 2017;153:69-80.
22. Kamilaris A, Prenafeta-Boldú FX. Deep learning in agriculture: a survey. Computers and Electronics in Agriculture. 2018;147:70-90.
23. Chlingaryan A, Sukkarieh S, Whelan B. Machine learning approaches for crop yield prediction and nitrogen status estimation in precision agriculture: a review. Computers and Electronics in Agriculture. 2018;151:61-69.
24. van Klompenburg T, Kassahun A, Catal C. Crop yield prediction using machine learning: a systematic literature review. Computers and Electronics in Agriculture. 2020;177:105709.
25. Richetti J, Diakogianis FI, Bender A, Colaço AF, Lawes RA. A methods guideline for deep learning for tabular data in agriculture with a case study to forecast cereal yield. Computers and Electronics in Agriculture. 2023;205:107642.
26. Akkem Y, Biswas SK, Varanasi A. Smart farming using artificial intelligence: a review. Engineering Applications of Artificial Intelligence. 2023;120:105899.
27. Balafoutis A, Beck B, Fountas S, Vangeyte J, Wal TVD, Soto I, *et al*. Precision agriculture technologies positively contributing to GHG emissions mitigation, farm productivity and economics. Sustainability. 2017;9(8):1339.
28. Saha D, Basso B, Robertson GP. Machine learning improves predictions of agricultural nitrous oxide (N_2O) emissions from intensively managed cropping systems. Environmental Research Letters. 2021;16(2):024004.
29. Oldfield EE, Eagle AJ, Rubin RL, Rudek J, Sanderman J, Gordon DR. Crediting agricultural soil carbon sequestration. Science. 2022;375(6586):1222-1225.
30. Sanderman J, Hengl T, Fiske GJ. Soil carbon debt of 12,000 years of human land use. Proceedings of the National Academy of Sciences of the United States of America. 2017;114(36):9575-9580.
31. Brummitt CD, Mathers CA, Keating RA, O'Leary K, Easter M, Friedl MA, *et al*. Solutions and insights for agricultural monitoring, reporting, and verification (MRV) from three consecutive issuances of soil carbon credits. Science of the Total Environment. 2024;912:169245.
32. LaCanne CE, Lundgren JG. Regenerative agriculture: merging farming and natural resource conservation profitably. PeerJ. 2018;6:e4428.
33. Giller KE, Hijbeek R, Andersson JA, Sumberg J. Regenerative agriculture: an agronomic perspective. Outlook on Agriculture. 2021;50(1):13-25.
34. Zhang X, Davidson EA, Mauzerall DL, Searchinger TD, Dumas P, Shen Y. Managing nitrogen for sustainable development. Nature. 2015;528(7580):51-59.
35. Tubiello FN, Karl K, Flammini A, Gütschow J, Obli-Laryea G, Conchedda G, *et al*. Pre- and post-production processes increasingly dominate greenhouse gas emissions from agri-food systems. Earth System Science Data. 2022;14(4):1795-1809.
36. Mulla DJ. Twenty five years of remote sensing in precision agriculture: key advances and remaining knowledge gaps. Biosystems Engineering. 2013;114(4):358-371.