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Earth Observation technologies for agricultural carbon credits: a review

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ABSTRACT

Earth Observation (EO) technologies offer accurate measurements of surface composition, enabling the monitoring of key variables linked to carbon credits, such as carbon content and sequestration potential. EO technologies also support the assessment of sustainable agricultural practices by tracking their impact on soil health and ecosystem dynamics. These practices enhance soil organic carbon content, promote biomass growth where applicable, and reduce greenhouse gas emissions, thereby contributing to carbon sequestration. These contributions can be recognized and incentivized through carbon credit systems. EO technologies provide continuous, high-resolution data, and can assist on accurately assessing numerus properties and therefore verify carbon credits, ensuring transparency and reliability in carbon trading markets. This review explores the pivotal role of EO technologies, mainly optical, in the assessment, generation, and verification of carbon credits within the agricultural sector, mainly croplands and aims to provide insights into the advantages of using EO for carbon credit assessment. These include, improved accuracy and reduced monitoring costs, while also discussing the limitations and potential solutions to overcome related obstacles. The findings highlight the transformative potential of EO in enhancing the credibility and efficiency of carbon credit systems, ultimately contributing to global climate change mitigation efforts.

1. Introduction

As the urgency to combat climate change intensifies, Earth Observation (EO) technologies are emerging as essential tools in monitoring, measuring, and verifying global carbon emissions. These innovations offer promising solutions to support international climate goals. The Paris Agreement, in 2015, committed 196 nations to limit global temperature rise to 1.5 °C [1]. To meet the objectives of the Paris Agreement, offsetting carbon emissions serves as a crucial catalyst for quickly implementing solutions in areas where they are most economically feasible, helping to bridge the period until our societies can fully transition away from Greenhouse Gases (GHG) emitting technologies. Carbon credits allow organizations to offset unavoidable emissions by supporting decarbonization projects [2]. Issued, monitored, and verified according to various standards, carbon credits provide the different stakeholders such as companies, farmers and NGOs, a reliable and transparent way to track and reduce their carbon footprint. Additionally, carbon credits facilitate essential funding for decarbonization projects worldwide, helping to achieve global climate targets while also supporting communities most affected by climate change, such as rural population, despite being the least responsible for it [3]. Despite significant progress in carbon credit markets, agriculture remains underrepresented in comparison to forestry, even though it holds substantial potential for carbon sequestration. To address this imbalance, there is a growing interest in integrating agricultural systems into carbon markets through more effective verification methods.

Agriculture plays a key role in combating climate change through carbon sequestration, where CO_2 is captured and stored in soil, plants, and biomass [4]. Sustainable practices like conservation agriculture, no-till farming, and cover cropping enhance soil carbon storage, improve soil health, and contribute to biodiversity [5,6]. As climate change mitigation efforts grow, carbon sequestration in agriculture becomes essential for building a sustainable, resilient food system [7]. Towards this goal, governments have sought to incentivize regenerative farming practices that enhance soil carbon sequestration and integrate farming into the carbon credit system. However, verifying these practices and translating them into carbon credits remains a challenge, particularly when compared to forestry systems, where carbon storage is

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easier to monitor.

Therefore, the carbon credit market has largely focused on forestry, which benefits from relatively straightforward monitoring of biomass and carbon storage. In contrast, agricultural systems are more complex, with greater variability in cropping practices, soil types, and carbon turnover cycles and for that reason, research remains sparse compared to forestry studies. This presents a significant challenge to integrating agricultural carbon sequestration into existing carbon credit frameworks. However, EO technologies, including satellite imagery, LiDAR, and drone systems, offer an innovative and scalable solution to monitor and verify carbon sequestration in agriculture. These technologies provide an opportunity to bridge the gap between agriculture and carbon markets by enabling precise, remote monitoring of large and diverse agricultural landscapes.

This paper aims to explore the role of EO technologies in agricultural carbon credit systems, focusing on their potential to revolutionize the generation, monitoring, and verification of agricultural carbon credits. By leveraging EO tools, we explore how these technologies can support the accurate estimation of carbon sequestration practices like conservation agriculture and cover cropping. We also examine the challenges, limitations, and potential solutions for integrating EO into the carbon credit framework. While the primary focus is on agricultural carbon credits, we also incorporate examples, studies, and protocols from more established sectors within the carbon credit market such as forests. By examining these key players, we aim to extract valuable insights and best practices that can be adapted or integrated into the agricultural carbon credit market.

First, we outline the methodology of this review. Then, we provide an overview of EO technologies and their application to estimating carbon sequestration in agricultural systems. Following that, we describe the carbon credit system and review the existing monitoring, reporting and verification (MRV) protocols. Finally, we discuss the integration of EO in carbon credits systems, highlighting benefits, challenges, and future directions for scaling up agricultural carbon credits.

2. Methodology

This review synthesizes existing literature on EO and carbon credits to analyze key trends, challenges, and opportunities. A comprehensive search of relevant peer-reviewed articles, reports, and policy documents was conducted using databases such as Google Scholar, Scopus, and Google search engine. Keywords and Boolean operators were used to identify relevant studies, ensuring a broad yet focused coverage of the subject matter (e.g., "remote sensing" AND "carbon credits", "remote sensing" AND "carbon sequestration", "carbon credits" AND "agriculture"), while also searching for the terminology about carbon credit systems. Studies were selected based on their relevance to utilizing EO techniques for carbon estimations, prioritizing recent publications when available, while also incorporating seminal works. Grey literature and industry reports were included, where necessary, to complement academic findings. Rather than adhering to a systematic review framework, this review follows a narrative approach, which is more suitable for integrating diverse findings from technical, policy, and applied sources. The discussion highlights areas of consensus, discrepancies, and gaps in the literature, providing insights for future research and practical applications.

3. Earth Observation in agriculture

Earth Observation is essential for monitoring agricultural activities due to unique challenges not found in other sectors. Agricultural production is strongly influenced by seasonal patterns tied to the biological life cycle of crops. It also depends on factors such as soil type, climate conditions, and farming practices, all of which vary widely across locations and over time. Additionally, since agricultural productivity can rapidly change due to unfavorable growing conditions, monitoring systems must be timely, especially given the perishable nature of many agricultural products [8]. There are several key agricultural parameters that can be monitored with the use of EO technologies and could potentially be included as main or auxiliary parameters to carbon credits MRVs. Table 1 provides an overview of these with the respective references of studies and reviews.

The table clearly shows that EO techniques cover a wide range of parameters, thus can enhance the ability to monitor agricultural practices that contribute to carbon sequestration, ensuring reliable data for carbon markets. By improving the precision of carbon credit assessments, EO supports the development of more transparent and credible carbon markets, ultimately promoting sustainable agricultural practices.

3.1. *Application of Earth Observation techniques in carbon credit system*

One major challenge in nature-based carbon offsets is accurately tracking atmospheric carbon absorbed by soil and vegetation [20]. Traditional direct measurement methods are complex, time-consuming, costly, and destructive, making them unsuitable for large-scale monitoring [21]. EO offers a powerful set of tools for enhancing the accuracy, efficiency, and reliability of carbon credit systems in agriculture. By providing high-resolution, scalable, and continuous data, EO technologies help overcome many challenges associated with traditional methods of measuring and verifying carbon sequestration [22]. Ongoing research and technological advancements are likely to further integrate EO into carbon credit markets, promoting more effective climate change mitigation strategies.

3.1.1. *Evaluating carbon sequestration via soil organic carbon*

Estimating carbon sequestration requires both accurate assessment of soil organic carbon (SOC) content at a given time and detection of changes across time intervals. Beyond their climate relevance, higher SOC levels enhance soil health and agricultural productivity, creating synergies between mitigation and adaptation [23]. Handling EO data presents numerous challenges, prompting the EO community to continually develop innovative analytical methods aimed at improving the data's usability and effectiveness. The number of studies evaluating EO techniques combined with machine learning for SOC estimation has increased exponentially in recent years [24]. Selected examples are presented below; however, more comprehensive information is available in [24,25].

EO-based SOC estimation has progressed rapidly, driven by improvements in data accessibility and analytical techniques. A landmark step was the U.S. Geological Survey's 2008 decision to make the Landsat archive freely available, which catalyzed widespread use of multispectral imagery for carbon-related studies [26–30]. Since then, sensors such

Table 1
Key agricultural parameters that can be monitored via EO techniques and indicative references.

Agricultural parameter	Index	Reference
	NDVI	[9]
Crop health and vegetation monitoring	LAI	[10]
	Chlorophyll content	[11]
Soil condition	SOC	[12]
	Soil texture	[13]
	Biomass	[14]
Crop yield estimation	Crop phenology	[15]
	Yield prediction models	[16]
Irrigation and Water management	Evapotranspiration rates	[16]
	Crop type classification	[17]
Land use and crop mapping	Land cover change detection	[18]
	Field boundaries and plot delineation	[19]

as Sentinel-2, with its red-edge bands, have become central for SOC estimation, often in combination with machine learning approaches. However, challenges remain as hyperspectral data such as Hyperion demonstrated potential but struggled to detect SOC levels below 1 %, highlighting ongoing limitations for low carbon soils [31].

A key trend is the integration of spectral information with ancillary variables (e.g., topography, precipitation, land-use change) and advanced modeling approaches. Studies show that SOC stocks correlate with land cover dynamics, vegetation indices such as NDVI, and terrain attributes [32–36]. Machine learning and, more recently, deep learning techniques (e.g., random forest, extreme learning machines, deep neural networks) consistently outperform traditional regression models in predictive accuracy [30,37–40].

The recently launched EnMAP [41], PRISMA [42] and forthcoming sensors CHIME [43] and SBG [44] represent significant advancements in hyperspectral EO. These sensors provide high-spectral and spatial resolution data across a wide range of wavelengths, enabling more precise analysis of land surface characteristics. In terms of SOC estimations, they can enhance SOC mapping by detecting subtle variations in soil properties, such as organic matter content, moisture levels, and soil mineral composition such as carbonates. Their ability to capture fine spectral details allows for improved monitoring of soil health and carbon stocks, contributing to better assessments of ecosystem carbon sequestration potential. The increasing availability of EO and soil data will enable the development of global spatiotemporal SOC stock assessment and monitoring. Overall, while EO has advanced from simple spectral correlations to sophisticated AI-driven approaches, the persistent challenge is detecting small SOC changes in soils with low baseline carbon which is a critical frontier for agricultural carbon markets.

3.1.2. *Evaluating carbon sequestration via above ground biomass*

Above ground biomass (AGB) plays a critical role in the global carbon cycle, representing the carbon stored in living vegetation, including trees, shrubs, and crops. Accurate estimation of AGB is essential for understanding carbon sequestration processes and assessing ecosystem health [45]. Traditional estimation methods are destructive and time consuming or rely on allometric equations. EO technologies, such as optical, microwave and LiDAR data, have revolutionized the estimation of AGB by providing spatially comprehensive and cost effective methods to monitor vegetation cover and biomass changes over time. The link between AGB and SOC stocks is significant, as the decomposition of plant biomass contributes to SOC levels, influencing the soil's carbon sequestration potential [46].

Optical satellites such as Landsat 8 and Sentinel-2 have been widely applied, with Sentinel-2′s red-edge bands particularly valuable for biomass estimation. Studies show that combining multisource data (e.g., harmonized Landsat-Sentinel products, MODIS LAI) enhances accuracy for large scale AGB assessments [47,48]. High resolution commercial satellites (e.g., GeoEye-1, RapidEye, Pleiades, WorldView) have further demonstrated strong potential for localized applications [49,50,59–61, 51–58].

Microwave remote sensing has become increasingly important because Synthetic Aperture Radar (SAR) operates independently of cloud cover and illumination. Polarimetric SAR, especially at L-band, has proven effective for forest and crop biomass estimation [62–65]. The upcoming Biomass [66] and NISAR [67] missions are expected to deliver unprecedented temporal and spatial coverage, accelerating biomass monitoring for agricultural systems.

LiDAR complements these approaches by providing precise 3D structural information. UAV and ground-based LiDAR studies have shown exceptional accuracy in estimating crop biomass, achieving R^2 values above 0.9 in sugarcane, wheat, and barley [68–71]. LiDAR's potential increases further when integrated with hyperspectral or SAR data, enabling multi-sensor fusion approaches that capture both structural and biochemical vegetation properties [72–74].

Overall, EO applications for AGB have shifted from single sensor approaches toward multi sensor, machine learning driven frameworks that can capture the complexity of vegetation dynamics. Future advances will depend on integrating high-temporal SAR, hyperspectral sensors, and structural LiDAR data with AI techniques to provide robust, scalable biomass estimates for carbon credit accounting.

4. Existing methods for generating and verifying carbon credits in agriculture

Effective carbon sequestration in agricultural soils demands both increased carbon inputs and reduced losses. Farmers can achieve this by limiting soil disturbance and employing strategies like cover cropping, mulching, and sustainable nutrient management. This approach requires a significant shift from traditional farming methods. To help farmers make this transition, carbon credits have been used as a financial tool, providing compensation for their efforts [75]. Over the past years, agricultural carbon credit projects in the voluntary market have seen a substantial increase. However, generating and verifying carbon credits remains challenging as there is an increasing number of carbon registries and several private companies have recently introduced measurement, reporting, and verification (MRV) protocols in their services. These protocols are designed to compensate farmers for capturing carbon in agricultural soils as part of a broader climate change mitigation strategy and there is an entire market value chain (Fig. 1) to reach the corporate buyers of carbon credits [76].

To further explain the above figure, farmers play a crucial role in carbon markets by adopting practices that increase SOC, creating a potential revenue stream for low-margin agricultural sectors. In developed countries, practices like reduced tillage, crop rotation, and cover cropping enhance SOC, while smallholder farmers in emerging markets often use agroforestry to benefit both economically and environmentally [75]. Project developers recruit farmers, support sustainable practices, and manage legal, financial, and verification aspects, balancing costs and profitability while ensuring compliance with carbon credit standards [77]. In emerging markets, they often partner with nonprofits and local leaders [78]. Major food and agriculture companies are increasingly taking on the role of developers to decarbonize their supply chains and meet emissions targets [79]. Certifiers, like Verra, Gold Standard and others, review and approve projects to ensure they meet strict standards for accuracy and transparency, maintaining the integrity of the carbon markets [80]. Third-party verifiers conduct audits and site visits to ensure projects meet eligibility criteria [81]. Carbon credits are traded through marketplaces, brokers, and project developers. Marketplaces allow the purchase of credits, while brokers integrate carbon offset services into broader strategies. Project developers may also sell directly to buyers, sometimes using innovative methods like cryptocurrencies [82]. Corporate buyers use carbon credits to offset emissions, setting their own quality standards and working with certifiers and brokers to find suitable credits [83].

Integrating agricultural practices with carbon credit standards presents several challenges. These include difficulties in measurement and verification, variability in practices and their outcomes, and the lack of standardized protocols. Additionally, the cost of implementing these practices as alternatives to conventional ones is a concern. Farmers' hesitation to adopt these practices further complicates the process. All these issues must be addressed to ensure that carbon credits effectively contribute to contribute to the reduction of atmospheric CO_2 concentrations.

4.1. *Essential attributes and limitations in the design of robust carbon projects and protocols*

To achieve lasting global success, carbon markets must inspire confidence by accurately assessing carbon gains or reductions, and by effectively supporting emission reduction goals. This requires adherence to strict and transparent protocols for GHG emissions reduction and

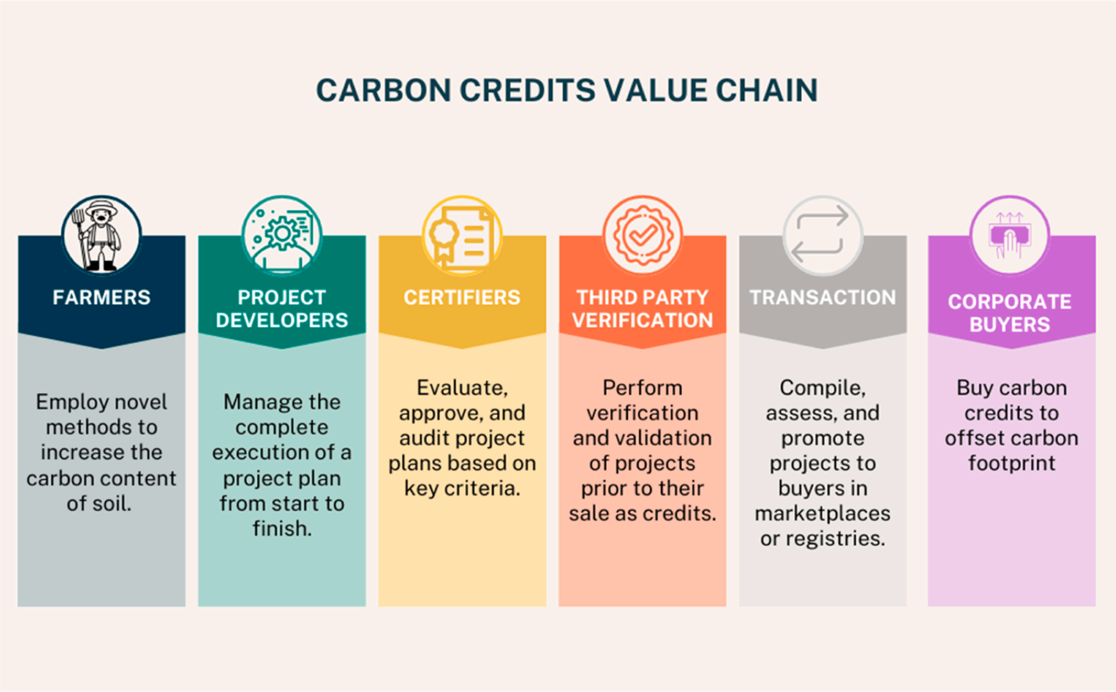

Fig. 1. Indicative carbon credits value chain from farmers to corporate buyers adapted from [34] *this may not apply to all carbon credit markets.

carbon sequestration. High quality carbon credits must meet rigorous standards, ensuring that the methods used to generate them are credible, measurable, and verified, fostering trust in their impact on climate goals. The following concepts are critical for ensuring the credibility and environmental integrity of carbon offsets.

Additionality: refers to the principle that a carbon offset project must result in emissions reductions or C sequestration that would not have occurred without the project's implementation. This ensures that the credits generated by the project represent genuine, extra environmental benefits. For a project to qualify as "additional," it must demonstrate that its carbon reductions are above and beyond what would have happened in the absence of the project, ensuring the integrity of carbon credits in offset programs [84].

Leakage: Leakage occurs when a carbon project reduces emission causing activities in one area, only for those activities (and their emissions) to be relocated to another area outside the project's boundary. This displacement undermines the overall effectiveness of the carbon project and must be avoided [85].

Permanence: refers to the long-term durability of the carbon reductions or sequestration achieved by the project. It ensures that the carbon removed or prevented from being emitted remains stored and is not re-released into the atmosphere. This concept is crucial, especially in projects like reforestation or carbon capture, where natural events (such as wildfires) or future land-use changes could reverse the gains. High-quality carbon credits require mechanisms to safeguard against such risks, ensuring the carbon benefits last over time [86].

No double counting: The GHG emission reductions or removals from a mitigation activity must not be counted more than once toward achieving climate targets. This prevents "double counting", which includes double issuance (issuing credits more than once for the same reduction), double claiming (more than one entity claiming the same reduction), and double use (using the same credit for multiple purposes) [87].

Transparency: The carbon crediting program must offer clear and detailed information on all credited mitigation activities. This information should be publicly accessible online and presented in a way that non-experts can easily understand, allowing for thorough review and transparency of the activities [83].

Robust quantification of emission reductions and removals: The GHG emission reductions or removals from the mitigation activity must be accurately quantified using rigorous, scientifically sound methods. This process should follow conservative approaches and ensure completeness to provide reliable and robust results [88].

4.2. Organizations and their respective protocols used in the carbon credit market related to agricultural soils

In the carbon credit markets, various protocols have been established to guide the measurement, reporting, and verification of carbon emission reductions. These protocols aim to provide standardized methodologies that ensure the integrity and transparency of carbon credits, allowing them to be traded with confidence across global markets. Below, we explore key examples of these protocols (Table 2).

4.2.1. The Verra protocol

Verra, a nonprofit corporation founded in 2007, leads the Verified Carbon Standard (VCS) Program. Its focus areas include blue carbon, carbon capture and storage, agriculture, forestry and other land use, and energy transition. One of the methodologies employed is the VM0042 [89] for improved Agricultural Land Management (ALM), which quantifies GHG emission reductions and SOC removals resulting from the adoption of improved ALM practices. A model is used to estimate GHG flux based on soil characteristics, implemented ALM practices, initial SOC stock measurements, and climatic conditions in the sample units. The biophysical inputs for the model, such as SOC, bulk density, and climate variables, are obtained through analytical methods, including dry combustion, proximal sensing techniques, direct sampling, and published soil maps. Additionally, there is recommended guidance on model calibration, validation, and uncertainty referred as "VMD0053" for the methodology for improved agricultural land management and the "VMD0021" module for the estimation of stocks in the soil carbon pool [90].

4.2.2. The Gold Standard soil organic carbon network

Gold Standard is a non-profit organization that sets standards and designs methodologies to credibly measure the impact of projects aimed

Table 2
Overview table of the organizations involved into the carbon credit system and their protocols.

Protocol / Organization	Scope / Focus	MRV Methods	Scale of Application
Verra (VCS, VM0042)	Agriculture, forestry, land use, blue carbon, energy transition	Model-based SOC estimates, soil sampling, proximal sensing, calibration/ validation modules (VMD0053, VMD0021)	Global; project-level, often medium to large farms
Gold Standard (Soil Organic Carbon Network)	Agriculture, sustainable land management, multi-impact projects	SOC sampling (ICRAF, VCS SOC module), bio-stimulant applications, improved tillage, organic amendments	Small-scale to industrial; flexible modular framework
FAO GSOC MRV Protocol	Farm-level agricultural landscapes	Lab methods (dry combustion, Walkley-Black, titration, colorimetry), remote/proximal sensing	Farm-level, adaptable for research institutions and agencies
Regen Network	Regenerative agriculture, ecological restoration, biodiversity	Remote sensing, ANN & ML models, soil spectroscopy, ecosystem proxies (AGB, NPP, PFT), soil erosion, nutrient and water runoff, and surface water quality	Global; farm to landscape level

at combating climate change and delivering sustainable development. It mainly focuses on impact rather than a specific mechanism; hence the standard can support the issuance of carbon credits and other financial tools. Gold Standard's framework functions as an 'umbrella methodology', providing a comprehensive set of requirements and guidance to maintain consistent quality across various activities undertaken by project developers. This framework also establishes the criteria for creating specific activity modules. It supports a wide range of applications, from small-scale, low-tech land use to large-scale, industrial land management. The methodology accommodates diverse SOC enhancement strategies, including improved tillage practices, the application of organic soil improvers derived from pulp and paper mill sludges, and the use of bio stimulants for soil revitalization. It follows the Soil Organic Carbon Framework Methodology version 1.0 and is based on two eligible protocols for soil sampling; the ICRAF protocol [91] and the VCS SOC module [92].

4.2.3. *The food and agriculture organization GSOC*

The "GSOC MRV Protocol: A Protocol for Measurement, Monitoring, Reporting, and Verification of Soil Organic Carbon in Agricultural Landscapes," released in 2020 by FAO/GSP and the Intergovernmental Technical Panel on Soils (ITPS), marks a significant advancement in soil management. This protocol addresses the growing need for standardized, reliable, and cost effective methods to measure and verify SOC changes and greenhouse gas removals from agricultural projects that adopt sustainable soil management practices at the farm level. Developed through research and global consultation, the protocol provides a framework for monitoring SOC stocks, supporting sustainable soil management practices, and enhancing agricultural resilience. While designed primarily for farm-level projects, the GSOC MRV Protocol is adaptable for use by various stakeholders, including research institutions, government agencies, and agricultural companies, to monitor and improve soil health and contribute to climate change mitigation efforts. The suggested measuring methods for SOC estimations include laboratory wet chemistry methods e.g. dry combustion, Walkley Black method, titration, and colorimetric methods and spectroscopic techniques (remote and proximal sensing) [93].

4.2.4. *The Regen Network*

Regen Network is a platform dedicated to ecological regeneration and sustainability. Its goal is to establish a transparent and reliable system for tracking, verifying, and incentivizing positive environmental outcomes, with a focus on regenerative agriculture, carbon sequestration, and ecosystem restoration. Regen Network applies blockchain technology to facilitate decentralized, peer-reviewed ecological data, ensuring the accuracy and reliability of environmental claims. The platform enables farmers and conservationists to document and validate improvements in ecosystem health, such as increased SOC or enhanced biodiversity. These improvements can then be converted into eco-credits, including carbon and biodiversity, which are tradable on Regen Network's marketplace [94]. One of the proposed methodologies for SOC estimation in Regenerative Cropping and Managed Grassland Ecosystems is the use of EO and machine learning. Specifically, this methodology protocol uses remotely sensed multispectral imagery (Sentinel-2) and soil sample results to train an Artificial Neural Network (ANN) to monitor changes in SOC stocks within a project area [95]. In addition to that, direct SOC measurements can be obtained through soil spectroscopy, laboratory tests, or farm management software like FarmOS, which integrates user-provided data such as soil color, farm practices, and sensor inputs. Additionally, various ecological indicators are proposed as proxies for detecting increases in SOC, including aboveground biomass (AGB), land conversion, net primary production (NPP), biodiversity, plant functional types (PFT), soil erosion, nutrient and water runoff, and surface water quality. SOC modeling is also considered to be enhanced using advanced RS techniques, such as spectral unmixing applied to hyperspectral Hyperion data [96].

5. Case studies of remote sensing data used in carbon credits

In terms of monitoring, reporting, and verification (MRV) mechanisms, EO data provide a scalable and effective approach to evaluate project performance. Early studies have mainly focused on forest carbon projects, and only a few peer-reviewed articles directly link EO data to the issuance of carbon credits. This reflects the earlier maturity of forestry protocols compared to agricultural ones. Nevertheless, the methodologies developed in forestry projects highlight both innovations and gaps that can guide the adaptation of EO approaches for agricultural carbon credit markets, particularly with respect to dynamic baseline construction, additionality testing, uncertainty management, and transparency. Below we summarize selected case studies and highlight the lessons they provide for agriculture.

A recently published conference paper, presented a structured methodology for implementing carbon offset projects, emphasizing three key stages: eligibility checks, performance benchmark calculation relative to a dynamic baseline, and the estimation of leakage liability. To address data accessibility and geographic scale challenges, the authors used Landsat-8 data and focused on agroforestry systems (AFS) in Brazil, where pastures have replaced primary rainforest over the past 50 years. The study implemented a dynamic baseline approach, allowing continuous monitoring of carbon stock regeneration in treatment and control plots, and introduced a statistical method for assessing additionality using the stocking index (SI), an NDVI based slope comparison, between treatment and control areas. The results quantified additionality while accounting for exogenous influences, and placebo areas were used to validate control plot matching. However, although the SI was effective for detecting differences between treatments, it was not directly proportional to carbon storage. To achieve reliable sequestration estimates, the authors suggested complementing indices with other EO datasets (e.g., GEDI, SAR, optical time series) and carefully calibrated allometric models. For agriculture, this study illustrates the potential of EO in developing dynamic baselines and robust additionality tests. It also highlights the challenges of translating spectral indices into accurate soil or biomass carbon values which is of particular importance for cropland and grassland systems [97].

Building on these methodological advances, the MIT Climate and Sustainability Consortium, in partnership with Banco Bilbao Vizcaya Argentaria (BBVA) and IBM Research, explored how EO and AI could scale beyond single pilot sites to support robust voluntary carbon markets. Their white paper examined two afforestation projects in Colombia (CUMARE) and Uruguay (GUANARE), estimating sequestration potential using spaceborne LiDAR data. Advanced geospatial analysis identified spatial heterogeneity in carbon storage and revealed inconsistencies in registry documentation, pointing to the need for standardized reporting. By comparing ground-based and satellite data, the research demonstrated both the feasibility and the necessity of spaceborne LiDAR (e.g., GEDI) to enhance accuracy and transparency. Although forestry-focused, the study's findings are directly relevant for agriculture, as agricultural systems also display strong spatial variability in management practices and soil carbon changes. EO supported approaches that account for in field heterogeneity and reporting standardization would strengthen the credibility of agricultural carbon credits [98].

While forestry case studies highlight transferable lessons, agricultural applications are also beginning to demonstrate how EO can be operationalized in MRV pipelines. Indigo Ag's carbon project, CAR1459, designed under the Climate Action Reserve's Soil Enrichment Protocol, provides one such example. The project combined the DayCent-CR biogeochemical model with field data to simulate carbon and nitrogen fluxes and developed an MRV pipeline integrating EO data (Harmonized Landsat Sentinel-2, HLS) for management practice verification, soil sampling, and statistical modeling. By accounting for uncertainties in soil carbon estimates and variability in management practices, the project issued 296,662 tCO_2e credits from an initial estimate of 398,408.5 tCO_2e, primarily from SOC improvements. The spatial and temporal variability in outcomes, for example differing impacts of no-till and cover crops across regions, underscored both the potential and the complexity of agricultural MRV. This example illustrates how EO, combined with models and field measurements, can enable incentives that reward regenerative practices while providing a rigorous basis for credit issuance [99].

Insights from agricultural pilots can also be contrasted with experiences from forestry projects that faced credibility challenges. A study of California's improved forest management (IFM) protocol used EO datasets such as eMapR [100] and LEMMA [101], integrating field measurements, LiDAR, Landsat time series, and statistical modeling to assess carbon stocks. By comparing project areas with control regions, the study revealed discrepancies between reported carbon stocks and EO based estimates. Project developers reported accumulation rates more than double those derived from satellite data, raising concerns about additionality and potential over crediting due to natural carbon accumulation. For agriculture, this underscores the importance of establishing EO-supported counterfactual baselines that distinguish management driven carbon changes from natural variability. Without such baselines, both forestry and agricultural projects risk overstating climate benefits [102].

Although there are limited studies linking EO technologies specifically to the issuance of carbon credits directly, numerous organizations involved in carbon credit projects already employ this technology primarily for MRV purposes. These companies use EO tools, such as satellite imagery and LiDAR, to track carbon sequestration and project monitoring, yet they often do not publicly disclose the detailed methodology and results from these assessments as peer reviewed articles. The lack of transparency regarding the outcomes of EO based MRV efforts leaves a gap in understanding how effectively this technology can be applied to improving carbon credit evaluations.

Taken together, these case studies show that EO has already demonstrated its potential to improve baseline setting, detect additionality, and address uncertainty, but also that methodological challenges persist, particularly in linking spectral data to actual carbon pools, ensuring permanence, and standardizing reporting. For agriculture, the adaptation of these lessons is urgent. Agricultural systems exhibit higher temporal variability, greater management heterogeneity, and more complex soil–plant interactions than forestry systems. The integration of EO with field calibration and transparent reporting protocols will therefore be critical to build credible and scalable agricultural carbon credit markets.

6. Benefits of Earth Observation in carbon credits systems

EO offers several significant benefits for both agricultural carbon credit systems, enhancing the accuracy, transparency, and scalability of MRV processes. These benefits are crucial for the development of robust carbon credit systems that can ensure the integrity and reliability of the credits issued. How EO data can be linked with the essential attributes and limitations mentioned in Section 3.1 is described below:

1. **Enhancing the accuracy and precision in carbon monitoring:** EO provides high spatial resolution data, and could enable precise and dynamic monitoring of carbon storage and land use changes over large areas. This means accurately measuring above ground biomass, growth rates, carbon stocks and disturbances [103]. It could also provide large scale coverage, in contrast with ground-based methods, which means that it allows vast coverage of remote areas efficiently. This makes it ideal for large scale carbon offset projects, where traditional field measurements are cost prohibitive. In addition to this, EO techniques can provide high temporal resolution [104] that can assist in continuously track changes in vegetation and land management practices over time, offering a dynamic view of carbon sequestration trends. This is particularly important in agriculture, where seasonal changes and land-use variability can affect soil carbon content.
2. **Transparency and standardization:** EO technologies collect objective data that can reduce reliance on self reported information from project developers. This increases the credibility and transparency of carbon credit systems, as third party verification is based on standardized satellite data [105]. Additionally, a significant amount of EO data from platforms like Landsat, MODIS, Sentinel, EnMAP, PRISMA and newer systems like GEDI are often publicly available. This promotes transparency and allows for independent auditing and verification of carbon credits, enhancing trust in carbon markets.
3. **Reduced costs:** By reducing the need for frequent in field surveys, EO lowers the operational costs of verifying carbon credits. This is particularly beneficial for projects in remote or inaccessible areas, where manual monitoring is expensive and logistically challenging [106].
4. **Detection of management practices and disturbances:** EO can detect and monitor specific agricultural practices, such as reduced tillage or the implementation of cover crops, which are key factors in soil carbon sequestration [107]. For forest projects, it can track deforestation, reforestation, or forest thinning activities, helping verify that carbon offset projects are following best practices [108]. EO can also quickly detect natural disturbances such as fires [109], pest infestations [110], or droughts [111], which impact carbon sequestration potential. Early detection of such events allows for prompt response and necessary adjustments in carbon accounting.
5. **Enhanced permanence monitoring:** Carbon credit systems depend on the permanence of sequestered carbon, which requires long term monitoring to ensure that carbon stored in forests or soils is not re-released into the atmosphere. RS provides the tools for continuous, decades-long monitoring [8] of soil and plant carbon dynamics, ensuring that projects maintain their carbon sequestration goals over time.

6. **Data integration and automation:** SOC maps from EO data can be integrated with simulation models (like DayCent or Century, Roth C) [112,113] to better estimate carbon fluxes in soil and vegetation. This integration could enhance the accuracy of carbon credit calculations, accounting for regional and ecosystem-specific variables.
7. **Support for additionality and leakage detection:** EO helps assess whether the carbon sequestration achieved by a project is truly additional (i.e., would not have happened without the project). By comparing project areas to non-project control regions, EO can determine if the project's activities genuinely increase carbon sequestration [97]. For example, in forest carbon projects, leakage occurs when reducing deforestation or degradation in one area leads to increased deforestation elsewhere [114]. RS can monitor neighboring regions to detect signs of leakage, ensuring that carbon gains in one area are not offset by losses in another.
8. **Supporting innovative financial instruments:** EO data can support the development of financial instruments such as carbon insurance. If a natural disaster threatens the permanence of a carbon offset project, EO data can be used to quickly assess damage and determine insurance payouts, helping to mitigate financial risks for project developers [115].

In conclusion, EO technologies are instrumental in strengthening the integrity, efficiency, and scalability of carbon credit systems, both in agriculture and forestry. By improving the accuracy of carbon measurements, reducing costs, and providing a transparent and standardized method for MRV, EO can enhance confidence in carbon markets and encourage wider participation, including from small scale landholders, (Fig. 2).

7. Challenges and limitations

While EO technologies offer significant benefits for carbon credit systems, their implementation also comes with challenges and limitations that can affect the accuracy, reliability, and adoption of these tools in MRV processes. These challenges and limitations can be grouped into technical, economical, institutional/policy and equity/accessibility considerations.

From technical perspective, new satellites offer high resolution imagery, EO still faces limitations in capturing fine scale details, especially in complex ecosystems [116]. Subtle actions such as reduced tillage or minor crop rotations may not be visible from space, even though they affect soil carbon levels [117]. While EO is highly effective for estimating above ground biomass, measuring below ground carbon, particularly SOC in vegetated or non-bare areas, remains a major challenge [118]. Because SOC is central to agricultural carbon credit projects, this constraint highlights the need to combine EO with complementary approaches. Integrating EO with in situ measurements and simulation models is technically demanding, requiring calibration against ground data, which is often uneven in quality and availability across regions [119]. Poor calibration or sparse sampling can lead to substantial errors. Revisit frequency of satellites also varies: some sensors provide frequent updates, but others are hindered by longer intervals or persistent cloud cover, leaving gaps in temporal coverage that complicate monitoring of seasonal agricultural practices or short-term carbon changes [120]. Finally, EO data processing requires specialized expertise and computational capacity, which are not always accessible to project developers [119]. Another methodological issue is that EO frequently provides spatial averages, which can obscure fine scale heterogeneity in carbon sequestration. This is particularly problematic for agricultural systems where soil carbon stocks can vary significantly across fields or even within plots [121].

The challenges are also economic. While many satellite datasets are freely available, higher resolution or specialized products, such as airborne or UAV LiDAR and hyperspectral imagery, can be prohibitively expensive. These advanced datasets often demand expert analysis skills, adding further costs [122]. For small scale projects and those in developing countries, both the financial burden of acquiring high quality data and the investment required for computing infrastructure pose significant barriers. Dependence on external providers for EO analysis can also

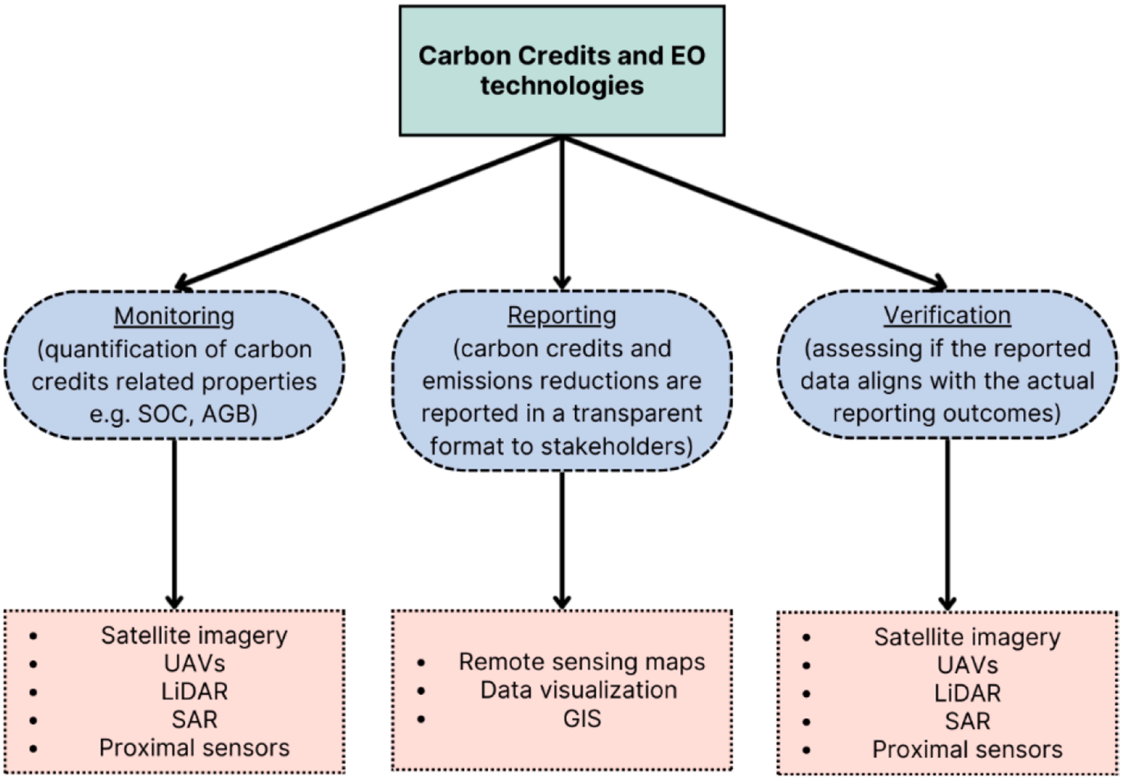

Fig. 2. Role of Earth Observation technologies across the Monitoring, Reporting, and Verification (MRV) process.

introduce recurring costs that limit the long-term feasibility of EO based MRV.

On the institutional and policy side, the absence of standardized protocols is a major limitation. Different projects frequently rely on different satellite datasets, processing methods, and assumptions, leading to inconsistent or non comparable results [86]. In some cases, EO is not used at all, further increasing methodological variability. This lack of harmonization hinders the establishment of reliable benchmarks and weakens confidence in carbon credit accounting. Even where EO is applied, validation through field based measurements remains necessary, but this can be challenging in remote, inaccessible, or highly heterogeneous project areas, adding uncertainty to the verification process [123].

Finally, there are important equity and accessibility concerns. Some stakeholders remain skeptical about the reliability of remote sensing compared with traditional field-based methods, slowing adoption and eroding trust in EO based approaches [124]. Moreover, the financial and technical resources required to use EO effectively mean that large organizations are better positioned to benefit, while smallholder farmers, indigenous groups, and local organizations risk being left behind [125]. Without deliberate efforts to lower barriers and ensure fair access, EO could reinforce existing inequalities in carbon markets rather than reducing them.

8. Potential solutions and future directions

The continued development of EO technologies is essential for overcoming current limitations in carbon credit systems. Emerging satellite systems and sensors, such as hyperspectral imagers or high resolution LiDAR, can provide more accurate and detailed data on vegetation, soil carbon, and land-use changes [126,127]. This will enhance the precision of carbon measurements and address issues like interference from soil background and canopy structure, fluctuations in optical vegetation signals, and the inadequate differentiation of functional traits caused by the lack of narrower spectral bands and small scale agricultural practices. The application of AI and ML to EO data can automate the detection and interpretation of land use patterns, carbon sequestration changes, and crop health monitoring. These tools can help process vast amounts of data, offering real-time insights and predictions about carbon stock changes [128].

To fully harness the potential of EO technologies in carbon markets, several policy initiatives should be considered. Establishing clear and consistent guidelines for the use of EO in MRV systems is essential [129]. This includes defining acceptable data sources, accuracy thresholds, and methods for integrating RS with ground-truth data. The creation of standardized and certified protocols will enhance comparability and confidence in carbon credits derived from EO data [130]. In addition to that, governments and regulatory bodies should encourage the use of EO technologies by offering incentives or subsidies for projects that implement these advanced monitoring systems. Policy frameworks could include tax breaks, grants, or technical support for small scale projects that adopt EO based MRV. EO technologies should be recognized and incorporated into global climate change frameworks and carbon accounting mechanisms. This would support the global scaling of carbon markets and ensure consistent use of technology across different countries [131].

In order to make EO technologies more accessible for smallholders and projects in developing regions, several strategies can be implemented starting with expansion of access to EO data. Although satellite data like Landsat, Sentinel, EnMAP and PRISMA already provide public access to high quality data, increasing the availability of higher resolution and more specialized datasets (e.g., from commercial satellites) would benefit smaller projects [132]. To tackle the issue of computational power, providing cloud based platforms for EO data analysis, can reduce the need for expensive local infrastructure. These platforms enable users to process large datasets without investing in high performance computing equipment, making it easier for smaller organizations to participate in carbon markets [133]. In close collaboration with universities and research institutions that have vast experience in EO research, offering training programs and technical assistance to smallholders, project developers, and local organizations can help build the expertise required to implement EO technologies effectively [134, 135]. Governments, NGOs, and private sector partners could collaborate to create certification programs for MRV operators, ensuring widespread understanding of how to apply EO tools.

Research is critical for advancing the integration of EO in carbon credit systems. Future research should explore ML methods, extended soil databases for model training and validation, spectral unmixing and different spectral methods to enhance the estimation of SOC through EO. Advancements in sensors or the integration of EO with ground based models could improve SOC estimation, particularly for agricultural carbon projects [136]. Research should also investigate how different ecosystems (i.e., wetlands, grasslands, and agroforestry systems) respond to EO monitoring. These ecosystems are often underrepresented in carbon markets, and improving the ability to measure carbon sequestration across diverse landscapes will expand the scope of carbon credits [137]. It is imperative to develop long-term monitoring solutions that can provide consistent, reliable data on carbon sequestration over decades. This is especially important for ensuring the permanence of carbon credits. Innovations in satellite technology, such as more frequent revisits and improved accuracy over time, will contribute to this goal. Further studies should focus on developing tools that can better detect leakage and verify additionality [97]. This includes using EO to monitor not just project areas but surrounding regions to identify if carbon reductions in one area are offset by increases elsewhere. In addition to monitoring changes in carbon stocks due to land restoration or improved management practices, EO also plays a critical role in verifying the permanence of existing carbon pools that are preserved from agricultural expansion or other forms of land-use change. Carbon can be issued for increasing carbon sequestration on marginal or degraded lands, but also for the protection of high carbon ecosystems, such as forests or wetlands, that would otherwise be at risk of degradation. Enhanced algorithms for comparing project sites to control sites could also help verify that carbon sequestration is truly additional to what would have occurred without the project. By addressing the challenges of EO in carbon credit systems through technological advancements, policy interventions, and strategic research, it is possible to make these systems more reliable, accessible, and efficient. This will not only improve the integrity of carbon markets but also support global efforts to mitigate climate change by promoting more accurate and widespread carbon sequestration practices.

Beyond research alone, future directions should also prioritize the integration of EO technologies with digital agriculture platforms and farm management systems, enabling farmers and project developers to directly link monitoring data with management decisions. This will help embed EO into operational practices rather than keeping it confined to academic applications. In parallel, stronger collaboration with private-sector carbon markets is needed to ensure that EO-based MRV is aligned with market requirements, improves transparency, and builds trust among buyers and investors. By positioning EO within these broader digital and market infrastructures, its uptake and practical impact can be significantly enhanced.

9. Conclusions

The growing accessibility of EO technologies, particularly through open access policies, has significantly advanced the field of C estimation in AGB or in soils. The integration of high-resolution imagery with sophisticated modeling techniques has allowed for more precise assessments of SOC stocks across diverse landscapes. While early studies showcased the potential of using satellite data for SOC mapping, recent advancements, such as the application of deep learning models and the combination of multispectral and hyperspectral data, offer promising new avenues for carbon prediction. As EO continues to evolve, it will play an increasingly critical role in monitoring SOC dynamics and AGB contributing valuable insights for both land management practices and carbon markets reporting for C sequestration in agriculture.

However, while EO has transformative potential for carbon credit systems by improving monitoring and verification, several technical, financial, and regulatory challenges must be addressed. Key research priorities over the next 5–10 years include refining EO methods for SOC estimation, integrating EO with farm level digital platforms, developing globally accepted MRV standards, and ensuring equitable access to EO tools in regions that have less data available. Overcoming these obstacles will require advancements in sensor technology, data processing capabilities, and the development of standardized, transparent protocols to ensure that EO can be effectively integrated into global carbon markets. If these gaps are addressed, EO technologies could become an indispensable tool for a transparent and trustworthy agricultural carbon market that is both scientifically rigorous and socially inclusive, ensuring that carbon credits deliver genuine and verifiable climate benefits.

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CRediT authorship contribution statement

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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