

Toward precise carbon management: current status, gaps and future directions

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Abstract The urgency of addressing climate change has underscored the need for precise carbon management—an approach that precisely monitors, assesses, and manages carbon emissions and sequestration at fine spatial, temporal, and sectoral scales. This perspective paper examines the current state of precise carbon management, highlighting advancements in ground-based observations, remote sensing, process-based model, and machine learning. Despite these innovations, key challenges persist, including data fragmentation and interoperability, limited geographical and temporal monitoring coverage, difficulties in integrating multi-source data sets with varying resolutions, and insufficient public engagement and decision-support infrastructure. To address these barriers, we propose a roadmap that includes the development of standardized data frameworks, expansion of monitoring networks in underrepresented regions, creation of a foundational AI model for carbon data integration, and user-centric decision-support tools to bridge science-policy gaps. Together, these proposed strategies aim to enhance the accuracy, scalability, and transparency of carbon management strategies in support of global climate goals.

Keywords near real time, high spatial resolution, carbon peaking and carbon neutrality, precise carbon management

1 Introduction

The occurrence of extreme events is unprecedented in the historical record and is expected to rise as global warming intensifies (IPCC, 2023). The escalating urgency of the

climate crisis has increased global efforts to mitigate carbon emissions and promote sustainable land-use practices (Gvein et al., 2023). However, the progress has been too slow across all areas of climate action, such as reducing greenhouse gas (GHG) emissions, strengthening resilience to a changing climate, getting the financial and technological support to vulnerable nations, according to the COP28 conference (i.e., the 28th Meeting of the Conference of the Parties (COP) to the UN Framework Convention on Climate Change (UNFCCC)). Under such a context, the COP28 conference brought renewed commitments from nearly all participating nations to accelerate climate action and enhance their emissions reduction targets. Every committed country submits a Nationally Determined Contribution (NDC) detailing its targets for reducing GHG emissions, where they were urged to strengthen these NDCs to close the “emissions gap” between current policies and the targets necessary to keep global warming below 1.5°C. Many industries submitted their sector-specific pledges and committed to reducing carbon emissions by phasing out routine fossil fuel combustion and transitioning to renewable energy sources (Saha et al., 2024). COP28 also underscored the importance of local communities and individuals in climate mitigation efforts. Grassroots initiatives, personal sustainability practices, and community-level resilience-building are expected to be part of the discourse.

Precise carbon management refers to the precise monitoring, assessment, and management of carbon emissions and sequestration at fine spatial, temporal, and sectoral scales. This approach enables stakeholders, from governments and industries to local communities and environmental organizations, to implement targeted interventions tailored to specific ecosystems, land-use practices, and socio-economic scenarios. As the focus of climate policy moves from pledges to implementations as a result of accelerated climate crisis, precise carbon

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management is playing and will continue to play a pivotal role in ensuring that mitigation targets are met by accounting for emissions and sequestrations covering large spatial range and capturing local entities in near real-time while appropriately integrating carbon capture and storage (CCS) technologies. Human induced-emissions of carbon dioxide to the atmosphere are the main cause of global climate change (Friedlingstein et al., 2023). Recently, detailed and spatially explicit estimates of major emission sources (e.g., fossil fuel combustion) have been updated in near real time, providing a spatial resolution of 0.1° and a temporal resolution of 1 day. Those data capture emissions from multiple sectors, including power generation, industry, residential consumption, ground transportation, domestic aviation, international aviation, and international shipping (Liu et al., 2020). Relatively speaking, the precise estimations of carbon dynamics from natural ecosystems are more challenging. Here we mainly focus on carbon management for precise natural ecosystems due to their complexity, dynamic nature, and the long-term consequences of ecological interventions.

As the world moves toward achieving ambitious net-zero carbon targets by mid-century, the need for precise carbon management is growing. For example, Nature-based Solutions (NbS) rely on leveraging natural ecosystems to mitigate climate change by enhancing carbon sequestration and reducing emissions through methods like reforestation, wetland restoration, and sustainable land management (Griscom et al., 2017; Lu et al., 2022). Precision is essential to accurately measure carbon sequestration, assess ecosystem health, and ensure the durability of carbon storage benefits over time. Additionally, the carbon credit market is designed to incentivize the reduction of carbon emissions and the sequestration of carbon through economic mechanisms. Entities that reduce their emissions beyond a set baseline can sell their surplus reductions as credits to those who are unable to meet their emissions targets (West et al., 2023). In the carbon credit market, accuracy in tracking and verifying carbon reductions is crucial to maintain trust and prevent issues like over-crediting and double-counting (Oldfield et al., 2022). Precision ensures that carbon credits reflect genuine reductions and help establish accurate baselines for projects. Furthermore, comprehensive monitoring, reporting, and verification (MRV) is essential for ensuring the accuracy, transparency, and accountability of carbon management efforts (Bellassen et al., 2015), especially in carbon markets and NbS. Precise carbon management enhances MRV by providing reliable, real-time data on carbon emissions and sequestration.

Recent technological innovations in ground-based sensor networks (i.e., eddy covariance towers and IoT (Internet of Things) Sensors), remote sensing (i.e.,

satellite monitoring, Light Detection and Ranging (LiDAR), hyperspectral Imaging, drones and Unmanned Aerial Vehicles (UAVs)), artificial intelligence (i.e., self-supervised learning and AI-driven predictive model), and process-based models have played a transformative role in the understanding of terrestrial carbon cycle (Lang et al., 2023; Li et al., 2023), and are also paving the way for a future widespread realizations of precise carbon management. For example, remote sensing platforms such as PlanetScope, RapidEye, and Skysat now provide satellite imagery with unprecedented spatial resolution, allowing for the identification of individual trees and the assessment of biomass changes at local scales (Li et al., 2023). LiDAR data have enhanced our understanding of three-dimensional forest structures, enabling precise estimation of aboveground carbon stocks (de Conto et al., 2024; Tolan et al., 2024). Drones equipped with cameras and multispectral sensors can provide highly detailed, localized, and frequent data on vegetation biomass and soil carbon (Deng et al., 2018), which is particularly useful for tracking the carbon sequestration potential of smaller or hard-to-reach areas. Additionally, high-performance computing systems and cloud-based platforms are essential for processing, storing and managing the vast amounts of data, enabling rapid analysis of global carbon data at high spatial and temporal resolutions. Overall, these technologies enable real-time monitoring, reliable carbon accounting, and transparent verification, making it possible to manage carbon more effectively across diverse ecosystems and industrial sectors. With these tools, carbon management can be more accurate, scalable, and actionable, ultimately supporting global climate goals and ensuring the integrity of carbon markets and nature-based solutions.

Precise carbon management faces several challenges rooted in the complexity of carbon science and the intricacies of measuring, monitoring, and managing carbon emissions and sequestration. Carbon stocks (the amount of carbon stored in ecosystems) and fluxes (the transfer of carbon between reservoirs) are influenced by a wide range of factors, including land-use change, agricultural practices, forest management, and industrial activities (Delgado-Baquerizo et al., 2017; Xu et al., 2021). These factors introduce variability into the carbon cycle, which complicates efforts to develop targeted and precise management strategies. Moreover, these dynamics vary significantly across different ecosystems, forests, grasslands, wetlands, and agricultural landscapes, necessitating high-resolution monitoring to capture the nuances of each system. Without such detailed information, conventional carbon management approaches risk overlooking critical sources and sinks, leading to inefficient or ineffective mitigation strategies. High-resolution monitoring technologies, such as ground-

based sensors, are crucial for effective carbon management but face limitations in spatial coverage and are often costly. Satellite data may miss small-scale changes in soil carbon or plant biomass. This gap in data hinders an accurate understanding of local carbon dynamics, leading to generalized models that may not reflect real-world conditions. Furthermore, process-based carbon models, which sometimes are not well parameterized and designed, struggle to capture fine-scale interactions like microclimates or disturbances, thereby creating uncertainty.

This paper provides a comprehensive review of the current status of precise carbon management, with a focus on technological advancements and methodological innovations. We examine key components of precise carbon management, such as remote sensing, *in situ* monitoring, and data integration techniques, and discuss their applications in different ecosystems. We also identify critical knowledge gaps, outline future research directions, and propose strategies to advance precise carbon management. By synthesizing the state of the field and proposing a path forward, this perspective aims to contribute to the development of more effective and inclusive carbon management strategies that are essential for meeting global climate goals.

2 Current status of precise carbon management

Precise carbon management has evolved rapidly over the past decade, driven by advances in observational technologies, data integration methodologies, process understanding and simulation, model-data integration and the advancements in artificial intelligence (AI) technologies (Fig. 1). It offers a transformative approach to tracking carbon stocks and fluxes, enabling precision management of emissions and sequestration efforts at scales previously unattainable. This section provides a detailed overview of the state-of-the-art technologies, methodologies, and frameworks that constitute the current landscape of precise carbon management.

Remote sensing provides continuous, large-scale spatiotemporal data to track vegetation dynamics, land use change, and carbon flux proxies over time. *In situ* measurements, such as eddy covariance flux towers, can be used to calibrate and validate remote sensing data and models, improving the accuracy of carbon flux estimates at key locations. Artificial intelligence methods, including machine learning and deep learning, can assimilate heterogeneous data sources, such as satellite imagery, meteorological inputs, and ground observations, to

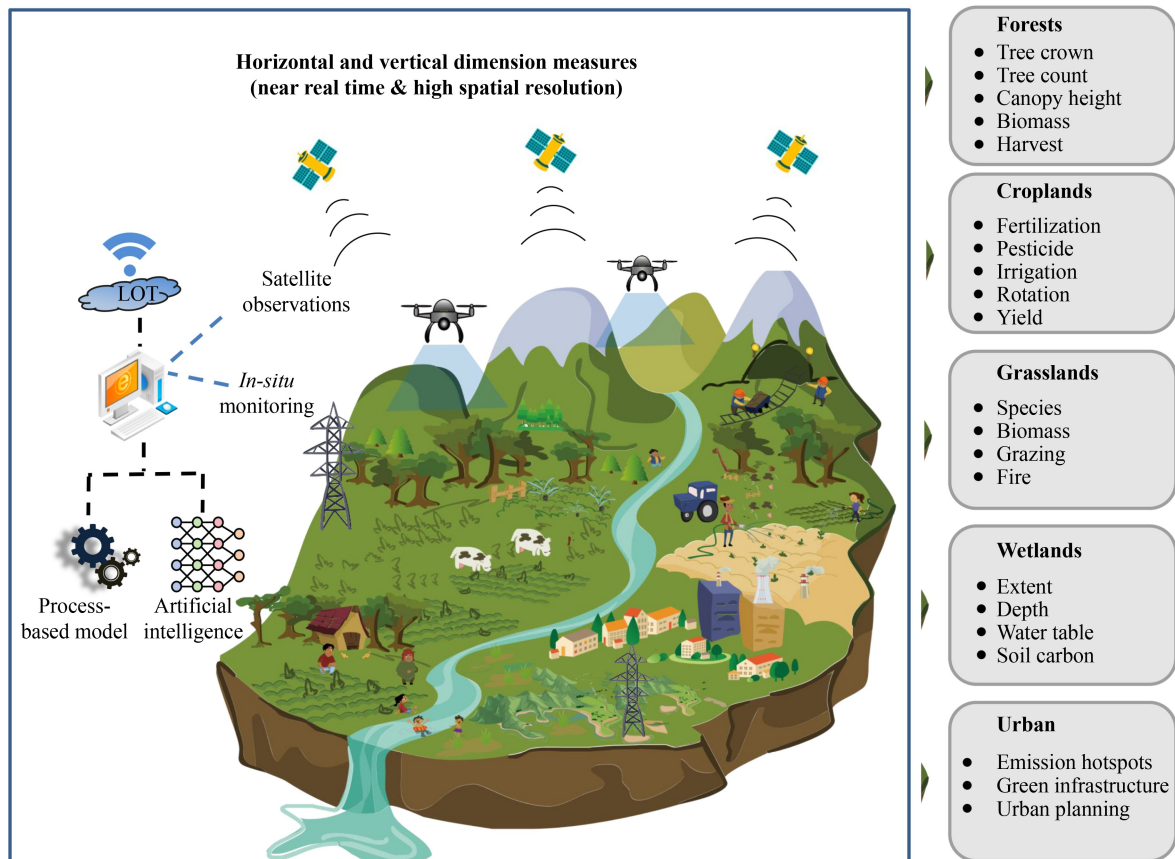


Fig. 1 A framework for precise carbon management through the integration of *in situ* monitoring, satellite observations, process-based model, and artificial intelligence.

identify complex patterns, fill data gaps, and generate high-resolution carbon maps. Meanwhile, process-based models offer a robust framework for simulating ecosystem carbon dynamics under different land management or climate scenarios. Integrating these complementary approaches can significantly enhance precise carbon management by leveraging their respective strengths while mitigating individual limitations.

2.1 Technological and methodological advances

2.1.1 *In situ* monitoring

Flux measurement networks such as FLUXNET (a global network of over 1000 flux towers spread across a wide variety of ecosystems, including forests, grasslands, wetlands, and agricultural areas) and ChinaFlux (China's national network of flux measurement stations, established to study carbon, water, and energy fluxes in key ecosystems across the country) play a critical role in improving our understanding of carbon exchanges between ecosystems and the atmosphere (Yu et al., 2006; Friend et al., 2007). Long-Term Ecological Research Networks (LTER) and the National Ecological Observatory Network (NEON) in the United States provide invaluable long-term data sets that help researchers understand ecosystem processes, providing insights into carbon sequestration trends and the impacts of land use change, climate variability, and ecosystem disturbance (e.g., wildfires, grazing (Vanderbilt and Gaiser, 2017)). For example, long-term studies of forests at the Harvard Forest LTER site have shown how increased atmospheric CO₂ concentrations enhance carbon uptake by trees, while warming accelerates soil carbon loss through increased respiration (Huang et al., 2020). This helps refine models that predict carbon cycle feedbacks under climate change scenarios. NEON provides long-term, high-resolution, and standardized data on carbon fluxes across a wide variety of ecosystems (Loescher, 2017). NEON's combination of data sources, from soil sensors to drones, can offer comprehensive insights into carbon dynamics at multiple scales. The near-real-time data provided by NEON on carbon fluxes is essential for tracking rapid changes in ecosystems, such as the effects of droughts or other climate extremes on carbon storage. The Integrated Carbon Observation System (ICOS) is a pan-European research infrastructure established to provide long-term, high-quality data on GHG concentrations and fluxes, enabling researchers to quantify the net carbon balance of different ecosystems (Heiskanen et al., 2022). This information is essential for understanding the contributions of various sectors (e.g., agriculture, forestry, land use) to overall GHG emissions.

High tower measurement networks consist of tall towers equipped with advanced instrumentation to measure various atmospheric gases, enabling high-

frequency measurements of carbon fluxes between ecosystems and the atmosphere (Lopez-Coto et al., 2017). These continuous data are crucial for understanding seasonal and annual variations in carbon uptake and release, which are also critical for validating and improving carbon cycle models. Manipulation experiment networks focus on experimentally altering environmental variables like CO₂ concentrations, temperature, and precipitation (e.g., DroughtNet) to study their effects on ecosystems, which are vital components in understanding carbon dynamics and enhancing precise carbon management strategies (Smith et al., 2024). By providing empirical data on carbon fluxes and ecosystem responses to water stress, experiments of DroughtNet provide valuable insights into the interactions between drought stress and carbon cycling.

In situ measurement provides highly precise, frequent, and site-specific data on carbon fluxes, helping researchers understand the role that different ecosystems play in carbon sequestration and how climate variables (temperature, precipitation, and solar radiation) affect carbon exchanges across different ecosystems, aiding in precise carbon management. These ground-based measurements are crucial for validating satellite-derived estimates and refining process-based models. However, the spatial coverage of flux towers is limited and unevenly distributed. Most towers are concentrated in certain regions (e.g., North America and Europe), leading to gaps in data from underrepresented areas like tropical forests or arid regions. Operating and maintaining flux towers is costly, and expanding coverage to new ecosystems is often hindered by financial challenges. This limits the ability to capture a more complete picture of global carbon fluxes.

2.1.2 Satellite observations

Remote sensing plays an increasingly critical role in precise carbon management by providing detailed, large-scale, and real-time data on carbon fluxes, land use, and ecosystem changes. Recent advancements in satellite technologies, sensor capabilities, and data analysis techniques have enhanced the accuracy and resolution of carbon tracking, allowing for better monitoring of carbon emissions and sequestration efforts (Fassnacht et al., 2024). Satellite missions such as NASA's Orbiting Carbon Observatory-2 (OCO-2) and ESA's Sentinel series have significantly improved our capacity to monitor atmospheric CO₂ concentrations and detect carbon sources and sinks at global and regional scales (Berger et al., 2012; Osterman et al., 2015). High-resolution satellite platforms, including PlanetScope, RapidEye, and Skysat, offer finer spatial resolutions, ranging from 3 to 30 m, allowing for the identification and analysis of individual trees, tree canopies, and vegetation structure (Brandt et al., 2020; Li et al., 2023).

Additionally, very-high-resolution commercial satellites such as Maxar's WorldView and Digital Globe's GeoEye provide sub-meter resolution data (Kongo and Pavlique, 2015; Hayden and Christy, 2023), enabling detailed mapping of land cover changes, deforestation, and urban expansion. In combination, these data sources facilitate precise estimation of aboveground biomass and support the development of carbon management strategies tailored to specific land-use scenarios.

Hyperspectral imaging can detect subtle variations in light reflectance that correspond to different pigments and biochemical compounds in plants, such as chlorophyll, water content, and nitrogen (Moharana and Dutta, 2016; Corti et al., 2017), providing additional insights into vegetation health and species composition. It also plays an important role in mapping and monitoring soil carbon by detecting various soil properties that correlate with soil organic carbon levels, such as soil moisture and texture. Airborne LiDAR has emerged as a critical tool for assessing aboveground biomass and carbon stocks, especially in forested ecosystems. By capturing three-dimensional canopy structure at fine spatial resolutions, LiDAR allows for the accurate measurement of individual tree height, canopy density, and understory vegetation (Wulder et al., 2012). These data are instrumental in estimating carbon sequestration potential and understanding the role of forests in mitigating climate change. LiDAR's ability to penetrate through canopy layers also makes it particularly useful for mapping complex ecosystems, such as tropical rainforests, where traditional optical sensors face limitations due to dense foliage.

Remote sensing allows for real-time or near-real-time monitoring of carbon emissions from sources like industrial facilities, wildfires, and deforestation activities. For example, during the 2020 Australian bushfires, the TROPOMI (Tropospheric Monitoring Instrument) on the Copernicus Sentinel-5P satellite sensor was used to track the massive CO₂ emissions released by the fires (Neyrizi et al., 2024), which measures the concentration of carbon dioxide and other greenhouse gases, like methane, in the atmosphere above the burning regions in near real-time. This data provides critical insights into the scale of emissions from the fires, helping scientists estimate the amount of carbon released into the atmosphere due to forest destruction. In the Amazon rainforest, the Brazilian government uses real-time satellite data from platforms like Landsat and Sentinel-1 to monitor deforestation activities, including detecting land-use changes, tracking forest cover loss, and estimating the associated carbon emissions (Doblas et al., 2020; Tang et al., 2023). These satellites can capture detailed imagery that shows where deforestation is happening, allowing for quick intervention by government agencies during periods of increased illegal logging or land clearing.

2.1.3 Process-based models

Process-based models can effectively simulate complex ecosystem processes such as photosynthesis, respiration, soil organic carbon decomposition, carbon transport and storage, and their interactions with evolving environment (Sun et al., 2021). By simulating how ecosystems respond to climate changes, these models can help forecast carbon sequestration potential and emissions under various climate scenarios. Process-based models can assess the impact of different land management practices (e.g., reforestation) on carbon stocks and fluxes, thus managers can evaluate the effectiveness of different strategies in enhancing carbon sequestration. Although process-based models offer the advantage of a mechanistic understanding and enable the attribution of effects to specific drivers or activities, they are often complex and computationally expensive. This complexity limits their application in large-scale studies with high spatial and temporal resolutions, which are essential for precise carbon management. Recent advancements in computational acceleration, such as matrix-assisted spin-up techniques (Huang et al., 2018a, 2018b; Luo et al., 2022; Liao et al., 2023) and machine learning-driven enhancements in computational efficiency (Sun et al., 2023), are likely to alleviate these computational bottlenecks. These innovations can help address the current limitations of these models, which have typically been restricted to specific studies with relatively low spatial resolution and long-term simulations at global or large regional scales. Driven by advances in computing power and data acquisition technologies, the resolution of process-based models has substantially improved. The integration of remote sensing and ecosystem modeling now enables the estimation of ecosystem carbon fluxes at relatively high spatial resolutions (e.g., 10 m and 30m) in specific regions and ecosystem types (Hurt et al., 2024; Wijmer et al., 2024). With growing high demands for the use of process-based models in precise carbon management, relatively complex process-based models such as ORCHIDEE and CLM (ELM) that couple water, carbon, nutrients and energy dynamics with multiple processes can simulate changes in ecosystem carbon stocks at a scale of 1 km or less, especially in highly heterogeneous environments by integrating high-resolution data sources and data assimilation techniques in the foreseeable future (Tan et al., 2010; Post et al., 2017; Li et al., 2024).

The integration of AI with process-based models has emerged in recent years and represents a significant advancement in facilitating precise carbon management by enhancing data integration and parameterization, improving predictive capabilities, and facilitating real-time monitoring and decision-making. Although process-based models can comprehensively reflect the dynamic processes of carbon sources and sinks in ecosystems and

provide mechanistic explanations for simulation results, there are common problems such as complex model structure, difficulty in obtaining and verifying parameters, and large computational requirements. AI has excellent capability at processing complex ecosystem data and optimizing model parameters, but it is often considered a “black box” and lacks physical interpretability. The benefits of process-based carbon models from AI include: 1) using AI to optimize parameters of process-based model; 2) using AI to replace some sub-processes of process-based models; 3) using AI to model the residual between the process-based model output and the observed value to correct the process-based model prediction results (Reichstein et al., 2019). The improvements of AI-based models from process-based (knowledge-driven) understanding include: 1) using the scientific knowledge of the output of process-based model as a constraint to train the AI model; 2) introducing physical knowledge in the design of the AI network structure to improve the interpretability of the AI model; 3) introducing physical constraints in the loss function to ensure the consistency of the intermediate or final results of the model with the laws of physics (Fang and Gentine, 2024). The combination of AI and process-based models, or the so-called hybrid modeling, has been successful in improving the accuracy and interpretability of prediction results and is an ongoing active field that can potentially bring more benefits for precise carbon managements (Karpatne et al., 2024).

2.2 Sectoral and ecosystem applications

Precise carbon management has demonstrated its value across various sectors and ecosystems, from forest management to agriculture, grassland, wetland conservation, and urban carbon tracking. For example, forests and wetlands are highly effective carbon sinks but require high-resolution remote sensing and LiDAR for structural monitoring. Agricultural systems benefit from AI-assisted yield modeling and soil carbon sensors, yet often face challenges due to seasonal variability and land-use intensity. Grasslands require cost-effective and scalable monitoring approaches, such as UAVs and spectral indices, while urban ecosystems rely on integrated sensor networks and land-use modeling to track anthropogenic emissions. This comparative analysis helps to illustrate the ecosystem-specific advantages, constraints, and management implications for implementing precise carbon strategies. The following sections detail specific applications in these areas.

2.2.1 Precise carbon management in forests

As remote sensing technology continues to evolve, the spatial and temporal resolution continues to improve, and it is possible to directly target individual trees. Detailed

mapping of individual tree crown areas, heights, and biomass has enabled more precise estimates of carbon sequestration potential and the impact of disturbances such as logging and wildfires. Airborne LiDAR data, which are capable of providing information on individual trees, have been used to develop high-resolution forest carbon maps that capture the spatial variability of biomass within forest stands (Ferraz et al., 2016). For example, aerial images were used to quantify crown size and carbon stock of each individual overstory tree in Rwanda, with an estimation of total 14.3 ± 2.8 Tg of aboveground carbon stocks in trees (Mugabowindekwe et al., 2023). U-Net deep learning model adapted for regression from high resolution optical images and LiDAR data sets can provide California tree height map at 0.6 m of spatial resolution, from which can access precise tree characteristics, such as crown size and location (Wagner et al., 2024).

The utilization of high-resolution data on forest age structure can facilitate the formulation of precise forest management decisions (Lin et al., 2023). These may include the harvesting of old-growth trees and the replanting of young ones at an optimal time, thereby ensuring the efficient and sustainable functioning of forest carbon sinks. To accurately assess biomass loss, it is essential to identify and manage forest disturbances effectively in order to mitigate carbon loss. Some natural disturbances, such as insect outbreaks and windstorms, are highly localized and transient phenomena (Curtis et al., 2018), which are often overlooked in lower resolution map classifications. Consequently, there is a pressing need for high-resolution forest disturbance data in order to accurately quantify biomass loss. Vatandaslar et al. (2024) used two processes that employed individual tree segmentation and area-based procedures based on LiDAR data are presented to estimate canopy cover across the Talladega Division of the Talladega National Forest (93694 ha) at the plot, stand, and landscape levels. However, these tools are inappropriate for broad-scale landscape assessments due to high costs and/or data policy issues (Vatandaslar et al., 2024). Yang et al. (2023) developed an approach to map tropical forest cover at a fine scale using Planet and Sentinel-1 synthetic aperture radar (SAR) imagery on the Google Earth Engine platform and used it to map all of South-eastern Asia's forest cover, which shows promise for monitoring forest changes, particularly those caused by deforestation frontiers (Yang et al., 2023).

2.2.2 Precise carbon management in agriculture

Agricultural practices significantly influence carbon dynamics through changes in soil carbon stocks and emissions from land management activities. Suboptimal farm management practices, such as inefficient fertilizer and pesticide application, poor livestock management,

and unplanned land-use changes are the driving forces which have led to increased greenhouse gases emissions from agriculture (Roy and George, 2020). Precision farming was developed to optimize resources utilization and minimize environmental impacts (Biswas et al., 2024). Variable rate technology enables farmers to apply different rates of fertilizer, seed, and other inputs at variable rates across different locations within a field. This approach focuses on plot precision, which can be targeted to increase soil organic carbon content and save on fertilizer application to reduce nitrogen emissions (Pawase et al., 2023). Moreover, yield monitoring systems have been demonstrated to be effective for crops such as corn, soybeans, wheat, and sorghum, thereby facilitating the assessment of crop productivity (McFadden et al., 2023). Furthermore, the integration of sensors and drone monitoring technologies with no-tillage techniques and cover crops (e.g., green manure) enables more precise regulation of soil disturbance frequency and extent through near real-time soil health assessment, thereby ensuring soil carbon accumulation (Huang et al., 2020).

The application of precision agriculture techniques has been demonstrated to enhance vegetation productivity, improve nutrient availability, and reduce greenhouse gas emissions. The potential of precision agriculture practices is directly linked to nutrient, land, and soil management. Researchers estimated the precision farming market already amounted to 2.3 billion euros in 2014 on a global level. It has been widely adopted in numerous countries, including the United States, the UK, France, Germany, Japan, and others (Srinivasan, 2006; Maloku, 2020). Analyses of agricultural emissions in the UK have identified nutrient management as the most promising method for reducing national GHG emissions by 3 Mt CO₂-eq by 2020 compared to 2007.

2.2.3 Precise carbon management in grasslands

High-resolution monitoring techniques, including satellite imagery and ground-based sensors, have been used to track carbon fluxes in grasslands and assess the impact of grazing intensity, fire management, and land-use changes. At the individual farm level, primary strategies employed in the context of carbon management in grasslands encompass the management of grazing activities and the designation of protected areas. The temporal concentration and spatial randomness of grazing activities necessitate the implementation of fine-grained monitoring strategies for the effective management of carbon.

Based on remote sensing data, grazing patterns and grassland vegetation cover can be observed, thereby enabling the adjustment of grazing strategies. For example, Ogungbuyi et al. (2024) employed Planet Laboratories SuperDove data to enhance the precision of Sentinel-2 imagery, which facilitates the observation of

grazing patterns at the individual farm level. Furthermore, the rational development of conservation strategies for land degraded areas can facilitate carbon sequestration and stabilize soil carbon stocks. The Great Green Wall Big Data Facilitator employs high-resolution satellite imagery to monitor vegetation restoration in African grasslands and desert areas, thereby providing reliable data and technical tools to support carbon stock enhancement and ecological restoration (Li et al., 2024b). Li et al. (2024a) used a machine learning scheme to estimate high-resolution grassland aboveground biomass across China with Sentinel-1/2 satellite images. Mofokeng et al. (2024) estimated the degree of grass curing in the Golden Gate Highlands National Park from 2016 to 2020 with high spatial resolution based on satellite data fusion, to analyze the fire danger index in protected grassland.

2.2.4 Precise carbon management in wetland and peatland

Wetlands and peatlands are essential ecosystems for climate regulation through long-term carbon sequestration (Chen et al., 2021; Zou et al., 2022). However, human activities, such as urban expansion, agriculture, and infrastructure development, threaten these ecosystems, potentially turning them from carbon sinks into carbon sources (Qiu et al., 2021). Restoring the hydrology of drained wetlands and peatlands through rewetting is essential for reversing carbon losses. Research shows that rewetting reduces emissions by restoring waterlogged conditions, which suppresses CO₂ release and promotes long-term carbon accumulation (Zou et al., 2022). In the Sacramento-San Joaquin Delta, California, rewetting of former agricultural land restored the ecosystem's ability to sequester carbon, demonstrating that degraded wetlands can transition back into effective carbon sinks over time (Valach et al., 2021). The Mukhrino Peatland in Western Siberia exemplifies the use of advanced monitoring tools to optimize peatland carbon management. Automated sensors continuously measure carbon fluxes, providing essential data on the peatland's role in regulating CO₂ and CH₄ emissions. Dyukarev et al. (2021) found that real-time monitoring supports adaptive management, ensuring that conservation efforts maintain the ecosystem's carbon sink function. This case highlights the importance of using technology for precise carbon management in peatlands.

Precision carbon management in wetlands relies heavily on technology to track changes in carbon dynamics and hydrological conditions. High-resolution remote sensing tools, such as the Sentinel-2 satellite, combined with ground-based sensors and machine learning models, enable real-time monitoring and forecasting of carbon fluxes, providing detailed information on wetland and peatland extent, water table, and vegetation biomass. Hu et al. (2018) highlighted the

importance of using satellite imagery to identify high-risk areas and monitor the effectiveness of restoration efforts over time. IoT-based sensors further enhance these efforts by collecting continuous data on water levels, soil conditions, and greenhouse gas emissions. This technology is particularly beneficial in peatlands, where fluctuating water tables can dramatically influence carbon release.

2.2.5 Precise carbon management in urban

Cities are significant contributors to global carbon emissions, responsible for nearly 70% of CO₂ emissions due to high energy consumption, transportation systems, and industrial activities (IPCC, 2015). To address this, many cities are adopting precision carbon management strategies, which combine satellite imagery, ground-based sensors, and atmospheric measurements to track emissions at a fine spatial scale. These advanced systems enable cities to identify emission hotspots, assess the impact of local policies, and optimize urban planning, ultimately helping to reduce their carbon footprints (Newman et al., 2017). Smart monitoring systems have integrated IoT sensors to monitor emissions in real time from sources like transportation and energy use in buildings, enabling authorities to quickly intervene in high-emission zones and refine policies as needed (Zhang et al., 2024). In addition to monitoring, urban green infrastructure plays a crucial role in carbon sequestration. Urban forests, parks, and green roofs help absorb CO₂, offsetting emissions from other sectors. A study in Melbourne demonstrated that green infrastructure could sequester up to 8% of the city's annual CO₂ emissions, emphasizing the importance of preserving and expanding these spaces (Livesley et al., 2016). Similar initiatives have highlighted the effectiveness of large-scale urban tree planting in reducing emissions and promoting sustainability. In New York City, high-resolution carbon mapping has been used to identify high-emission areas and evaluate the effects of policies like congestion pricing and building energy efficiency regulations. Satellite data, combined with air quality sensors, revealed a 12% reduction in emissions over four years, providing city planners with insights into the efficacy of these measures (Chrysoulakis et al., 2013). These case studies illustrate how high-resolution monitoring and refined carbon management strategies are helping cities around the world address their carbon emissions more effectively.

3 Knowledge gaps in precise carbon management

Despite the rapid advancements in precise carbon management technologies and methodologies, several critical knowledge gaps continue to impede their

widespread implementation and effectiveness. Addressing these gaps is essential for realizing the full potential of high-resolution approaches in supporting carbon mitigation and adaptation strategies at local, regional, and global scales. This section highlights the key knowledge gaps that need to be bridged, including data fragmentation, interoperability issues, limited geographical coverage, and the challenges associated with long-term monitoring and stakeholder engagement (Fig. 2).

3.1 Data fragmentation and interoperability

One of the key challenges in precise carbon management is the fragmentation and inconsistency of carbon data across various platforms, scales, and sources (Borghei, 2021). This issue stems from several factors: First, there is often a lack of standardized frameworks for carbon data collection, processing, and reporting, which makes it difficult to compare and integrate data sets from various sources. Second, carbon data are often stored in separate, restricted repositories, creating barriers to data sharing and accessibility; this limits collaboration and impedes the development of integrated carbon management strategies. Third, interoperability challenges arise from differences in data scale, quality, and accuracy, complicating the integration of remote sensing data, *in situ* measurements, and models. These issues require advanced data fusion techniques that are not yet widely adopted.

3.2 Limited geographical and temporal coverage

Limited geographical and temporal coverage in carbon management poses significant challenges. First, monitoring has primarily focused on regions with established infrastructure, like North America and Europe, leaving crucial areas such as tropical forests and high-latitude areas, due to factors like cloud cover, lack of infrastructure, and limited resources in developing and underdeveloped regions underrepresented. Second, temporal gaps in monitoring, as most data are from short-term or sporadic studies, prevent a comprehensive understanding of long-term carbon dynamics and complicate the assessment of mitigation strategies and future carbon projections.

3.3 Data integration and uncertainty quantification

Precise carbon management relies on the integration of data from multiple sources, including satellite observations, *in situ* measurements, and process-based models. However, combining these data sources presents several analytical challenges. First, there often exist scaling discrepancies between remote sensing data and *in situ* measurements operating at different spatial and temporal scales (Wu and Li, 2009). For example, satellite

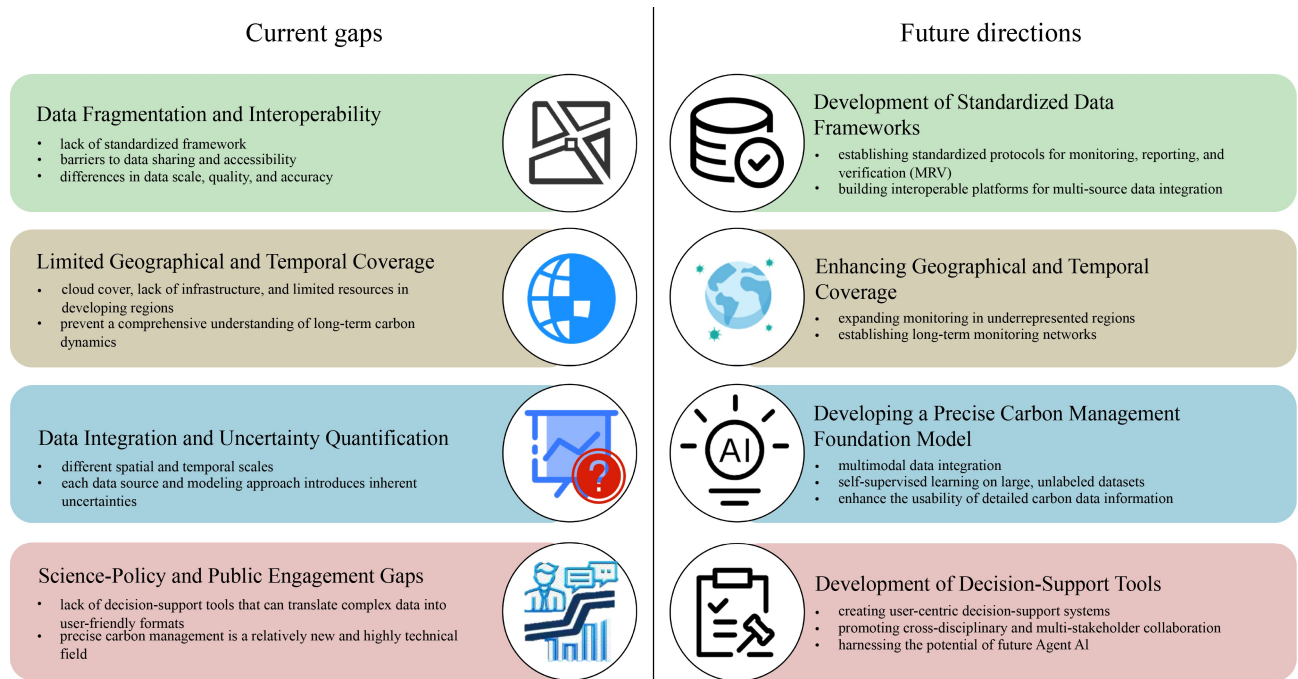


Fig. 2 The critical knowledge gaps and future research directions in precise carbon management.

data may provide coarse-scale information over large areas, while *in situ* sensors capture fine-scale data at specific locations. Integrating these data sets to produce consistent, high-resolution carbon maps requires advanced scaling techniques that account for these discrepancies. Second, each data source and modeling approach introduces inherent uncertainties due to measurement errors, sampling biases, and model assumptions (Moudrý et al., 2024). Quantifying and propagating these uncertainties in integrated assessments is a major challenge, as it requires robust statistical methods and comprehensive sensitivity analyses that are not yet widely applied in precise carbon management studies.

3.4 Science-policy and public engagement gaps

Data visualization and interactive platforms are powerful tools for raising awareness, yet there is a paucity of decision-support tools that can translate complex data into user-friendly formats for policymakers, land managers, and other stakeholders, thereby creating a significant disconnect between the scientific advancements in precise carbon management and their translation into actionable policies and public understanding. Additionally, precise carbon management is a relatively new and highly technical field, making it challenging to communicate its significance to non-experts, leading to a lack of public support for carbon management initiatives and hindering the adoption of best practices at local and regional levels. Community-based initiatives and public engagement tools illustrate how local participation and awareness efforts can effectively connect climate action with tangible

community benefits and promote individual behavior change. Citizen science, where individuals participate in data collection and local monitoring can contribute to climate and carbon research. Efforts to enhance science communication, through educational campaigns and stakeholder engagement, are necessary to build broader support for precise carbon management (McKinley et al., 2017). Fostering collaboration and communication across disciplines and sectors will be essential for bridging the science-policy divide and promoting the adoption of precise carbon management.

4 Future research directions

To harness the full potential of precise carbon management and address the gaps identified in current methodologies, a multi-faceted research agenda is needed. For data integration, we emphasize the need to develop standardized protocols and interoperable data infrastructures that can link *in situ* measurements, remote sensing products, and model outputs. We also highlight the potential of open-access data platforms and cloud-based processing systems to support large-scale carbon assessments. To address technological limitations, we recommend increased investment in high-resolution and low-cost sensors, the integration of AI with physical models to enhance predictive accuracy, and efforts to improve the calibration and validation of remote sensing products across diverse ecosystems. Regarding interdisciplinary collaboration, we propose the establishment of cross-sectoral research hubs and pilot projects that bring together ecologists, remote sensing

experts, data scientists, and policymakers. We also suggest the development of shared terminologies, co-designed workflows, and joint training programs to bridge disciplinary divides. This section outlines key research priorities and strategies to advance precise carbon management toward achieving global climate goals (Fig. 2).

4.1 Development of standardized data frameworks

4.1.1 Establishing standardized protocols for monitoring, reporting, and verification (MRV)

The lack of standardization in data collection and reporting has been a persistent barrier to precise carbon management (Al-Qaseemi et al., 2016). To address this, the research community should prioritize the development of universal protocols and methodologies that facilitate data harmonization across regions, ecosystems, and sectors. These protocols should include guidelines on data formats, measurement techniques, and metadata standards, ensuring that data collected from different sources can be easily integrated and compared. One promising approach is to establish standardized protocols for MRV, which involves creating consistent and reliable systems to track and assess the outcomes of climate actions, such as carbon emissions reductions and carbon sequestration (Bellassen et al., 2015). MRV protocols are essential for ensuring that data on greenhouse gas (GHG) emissions and removals are accurate, transparent, and verifiable, especially in the context of carbon management and climate mitigation projects.

4.1.2 Building interoperable platforms for multi-source data integration

A key research priority is the development of interoperable platforms that enable seamless integration of data from satellites, ground-based sensors, and process-based models (Luers et al., 2022). These platforms should support advanced data fusion techniques, such as machine learning-based feature extraction and multi-scale modeling, to create comprehensive, high-resolution carbon maps. Collaborative initiatives like the Global Carbon Atlas or the Forest Observation System could serve as models for building such platforms, leveraging cloud computing and distributed databases to handle large volumes of data and provide real-time access to users around the world.

4.2 Enhancing geographical and temporal coverage

4.2.1 Expanding monitoring in underrepresented regions

Achieving comprehensive global carbon management

requires expanding monitoring efforts in underrepresented regions such as tropical forests, drylands, and polar areas, which are critical to the global carbon cycle. This involves targeted investments in satellite missions equipped with advanced cloud-penetration technologies (e.g., Synthetic Aperture Radar) and enhanced spatial and temporal resolutions. Field-based initiatives should also be implemented in collaboration with local communities to establish long-term monitoring sites in these areas. Strengthening local capacity by providing affordable monitoring tools, like low-cost IoT sensors, will enable these regions to actively contribute to global carbon management.

4.2.2 Establishing long-term monitoring networks

Additionally, a global network of monitoring sites must be developed to track key carbon variables, such as soil organic carbon, biomass, and atmospheric CO₂ concentrations, over time. This network should integrate existing programs (e.g., FLUXNET) with new sites and leverage automated technologies to minimize costs and ensure data consistency. The comprehensive long-term data sets generated will enhance carbon model accuracy and support informed decision-making for future climate and land-use management.

4.3 Uncertainty quantification and foundation model development

4.3.1 Quantifying and reducing uncertainty in carbon assessment

Uncertainty quantification is a critical component of data integration in precise carbon management, as it helps assess the reliability of estimates derived from heterogeneous sources. Several advanced statistical and computational methods have been developed for this purpose. Bayesian hierarchical models allow for the combination of multiple data types while explicitly modeling uncertainty at each level, making them particularly useful for regional-scale carbon flux estimation. Monte Carlo simulations are widely used to propagate uncertainty through carbon budget calculations by repeatedly sampling from probability distributions of input variables. Ensemble approaches, such as those used in global vegetation models or remote sensing-based biomass estimates, provide a range of possible outcomes by aggregating multiple model outputs, helping to capture variability and reduce overfitting. Additionally, data assimilation techniques, such as the Ensemble Kalman Filter, can merge observational data (e.g., from flux towers or satellites) with process-based models in near real time, continuously updating predictions and quantifying associated uncertainties.

4.3.2 Developing a precise carbon management foundation model

Developing a precise carbon management foundation model (PCM-FM) could be a critical next step in achieving comprehensive, precise carbon monitoring. A PCM-FM could leverage diverse data sets from satellites, ground-based sensors, and process-based models to create an integrated view of carbon dynamics across various ecosystems. This enables it to monitor carbon dynamics across multiple scales (e.g., global, regional, local) and within various ecosystems, such as forests, grasslands, wetlands, and agricultural landscapes. Such multimodal data integration helps to gain a deeper understanding of carbon fluxes and storage mechanisms, facilitating precision management in ways that would be difficult to achieve with single-source data. Additionally, PCM-FM has a potential to address the challenge of limited labeled data for downstream tasks by inherently enhancing efficiency through self-supervised learning on large, unlabeled data sets. This training approach allows for subsequent fine-tuning with smaller, task-specific data sets, thereby reducing the need for extensive labeled data (Moor et al., 2023). Such a method not only accelerates the adoption of AI in carbon management but also improves the model's accuracy, robustness, and reliability, providing valuable tools for precise carbon management.

PCM-FM also enables translate complex data into user-friendly formats for policymakers, land managers, and other stakeholders. This will help bridge a critical gap that currently limits the practical application of precise carbon management insights in real-world decision-making processes. By transforming detailed carbon data into accessible visualizations and summaries, PCM-FM could enhance the usability of this information, making it easier for stakeholders to incorporate these insights into strategies for carbon mitigation and sustainable land management.

4.4 Development of decision-support tools

4.4.1 Public engagement in carbon management

Enhancing public understanding and participation is essential for the legitimacy, transparency, and effectiveness of carbon management. Effective strategies include citizen science, interactive data visualization, community-based initiatives, and awareness campaigns. These approaches foster public involvement in data collection, improve accessibility to carbon information, and promote informed behavioral change. When supported by appropriate tools and communication strategies, public engagement plays a critical role in advancing precise carbon management across scales.

4.4.2 Creating user-centric decision-support systems

To bridge the gap between high-resolution carbon data and their practical application, future research should focus on developing user-centric decision-support systems tailored to the needs of various stakeholders, including policymakers, land managers, and conservation practitioners (Mistry and Berardi, 2016; Mugabowindekwe et al., 2024). These systems should integrate high-resolution data, predictive models, and scenario analysis tools to provide actionable insights that support decision-making at local, regional, and global scales.

Research should also explore the use of visualization techniques, such as interactive dashboards and geospatial data platforms, to facilitate the translation of complex scientific data into clear, policy-relevant information, supporting the development of targeted interventions for carbon management and climate adaptation.

4.4.3 Promoting cross-disciplinary and multi-stakeholder collaboration

Advancing precise carbon management requires fostering cross-disciplinary collaboration, strengthening public-private partnerships, and ensuring equity and inclusivity. Integrating expertise from fields such as remote sensing, ecology, atmospheric science, data science, and economics is essential for advancing precise carbon management. Each discipline plays a distinct and complementary role: remote sensing provides spatially explicit and scalable data critical for ecosystem monitoring; ecology deepens our understanding of carbon fluxes, sequestration processes, and ecosystem responses; data science and AI enable the integration, modeling, and uncertainty quantification of heterogeneous data sets; while economics and policy studies contribute to the design of incentive structures, market-based instruments, and regulatory frameworks. Interdisciplinary collaboration helps address practical challenges, such as aligning technological capabilities with local governance contexts and developing decision-support tools that are both scientifically robust and operationally usable. These efforts are increasingly supported by interdisciplinary research centers and collaborative platforms, which aim to scale carbon management strategies globally and align them with broader sustainability goals (Eweje et al., 2021). Public-private partnerships should drive innovation, deploy monitoring infrastructure, and create data-sharing platforms, with mechanisms like carbon credits and green financing encouraging private sector investment. Ensuring equitable access to low-cost technologies, capacity-building programs, and high-resolution data empowers underrepresented regions to actively participate in carbon management efforts. Furthermore, integrating the perspectives and knowledge of indigenous peoples and local communities enhances

inclusivity and promotes climate justice, enabling effective and equitable global carbon management.

4.4.4 Harnessing the potential of future agent AI

Virtual laboratories, wherein AI agents simulate and analyze complex systems within digital environments, have become a reality with the rapid advancement of AI technologies (Durante et al., 2024). AI agents offer great benefits in data collection, processing, management, analysis, prediction and decision-making across multiple tasks, ecosystems and scenarios. The deployment of multiple virtual AI agents across different environments greatly enhances the scope and efficiency of data collection, monitoring, pattern recognition, anomaly detection and other analyses. In addition to saving human labor and time, these agents can work collaboratively, sharing information and iterating on their tasks and analyses, which widens and deepens the analyses through collective learning from multiple distributed networks. These task divisions and interconnections ensure a comprehensive coverage of varied ecosystems and allow for the detection of localized changes in carbon dynamics with greater precision.

These virtual laboratories allow AI agents to refine their decision-making processes before real-world deployment, which enhances the efficiency of understanding, experimentation, and the development of novel solutions for carbon management. By creating digital replicates of real-world ecosystems, AI agents can simulate carbon dynamics, test mitigation strategies, predict outcomes, and accommodate multiple users' needs before applying them in practice. By designing and assigning multiple AI agents for hundreds of specific tasks (e.g., data receiving, communication, plot making, visualization, scenario design, etc.), the application of AI agents in carbon cycle has the great potential to tailor the needs of various stakeholders while facilitating optimization of policies and strategies to address carbon management challenges.

Moreover, by integrating AI agents with PCM-FM, the vision of future carbon management is to reach unprecedented scalability and flexibility. PCM-FM provide the tool and information needed to process high-resolution, heterogeneous data sets and offer insights into historical, current, and future carbon dynamics. AI agents, on the other hand, deliver the operational capability and realizations to respond to real-time changes and automate decision-making processes toward management goals. Together, these technologies will revolutionize the current MRV framework, providing multiple platforms and tools, improving transparency and enabling countries to meet their climate targets with greater accountability.

5 Conclusions

Precise carbon management is emerging as a pivotal approach in addressing the complex challenges of climate change. By providing detailed, spatially and temporally explicit high-resolution quantifications of carbon stocks, fluxes, and emissions, this approach enables the development of more targeted and effective strategies for carbon mitigation and sequestration. However, realizing the full potential of precise carbon management requires overcoming several technological, methodological, and policy-related barriers.

This paper has highlighted the significant advancements in precise carbon management, from *in situ* monitoring networks and remote sensing technologies to process-based and machine learning-based modeling approaches. We have discussed the state-of-the-art capabilities for mapping and managing carbon across diverse ecosystems and sectors, including forests, agricultural landscapes, and coastal environments. These technologies have facilitated more precise estimates of carbon stocks, better tracking of land-use changes, and a deeper understanding of carbon dynamics at local and regional scales.

Despite recent technological advances, several critical gaps continue to hinder the widespread implementation of precise carbon management. These include fragmented data systems and the lack of standardized protocols, limited spatial and temporal coverage, especially in data-scarce regions, and persistent difficulties in integrating multi-source data sets across varying resolutions, which lead to significant uncertainties in carbon estimates. Furthermore, the absence of accessible decision-support tools and limited public engagement present major obstacles to translating scientific insights into actionable policies.

To address these challenges, future efforts should focus on the development of standardized data frameworks for measurement, reporting, and verification (MRV), the expansion of long-term monitoring networks in underrepresented regions, and the integration of multimodal data sets through advanced AI techniques. In particular, foundational carbon management models, leveraging self-supervised learning and large-scale, unlabeled data sets, can improve the scalability and accuracy of carbon assessments. Equally important is the development of user-centric decision-support tools that can translate complex data into practical guidance for policymakers and practitioners. Interdisciplinary collaboration and public-private partnerships will be essential to accelerate innovation, reduce implementation costs, and ensure that carbon management strategies are both scientifically robust and socially inclusive.

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