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Review Article

A U.S. scientific community review of carbon cycle science gaps and opportunities to better support earth system science and carbon management

N.C. Parazoo [a,1,*], D. Carroll [a,b,1], J.B. Abshire [c,d], Y.M. Bar-On [e,f], R.A. Birdsey [g], A.A. Bloom [a], K.W. Bowman [a], R.K. Braghiere [a,e], L.M. Bruhwiler [h], B. Byrne [i], A. Chatterjee [a,j], D. Crisp [k], L. Duncanson [d], A.F. Feldman [c,d], A.M. Fox [c,l], C. Frankenberg [d], B.A. Gay [a], F. Hopkins [m], F.M. Hoffman [n], J.R. Holmquist [o], L.R. Hutyra [p], M. Keller [q], C.D. Koven [r], J.L. Laughner [a], J. Liu [a], N.S. Lovenduski [s], N. MacBean [t], G.A. McKinley [u], G. McNicol [v], D. Menemenlis [b], A.M. Michalak [w], C.E. Miller [a], H. Nesser [a], T. Oda [d,x], E.M. Ordway [y], L.E. Ott [c], K. Paustian [z], Z.A. Pierrat [a,aa], B. Poulter [ab], S.C. Reed [ac], D.S. Schimel [a], S.P. Serbin [c], S.S. Saatchi [a], H. Suto [ad], L. Windham-Myers [ac], D. Wunch [ae]

[a] Jet Propulsion Laboratory, California Institute of Technology, United States of America
[b] Moss Landing Marine Laboratories, San José State University, United States of America
[c] NASA GSFC, United States of America
[d] University of Maryland, United States of America
[e] California Institute of Technology, United States of America
[f] Weizmann Institute of Science, Israel
[g] Woodwell Climate Research Center, United States of America
[h] NOAA Earth System Research Laboratory, United States of America
[i] Qube Technology, United States of America
[j] Schmidt Sciences, United States of America
[k] Crisp Spectra, LLC, United States of America
[l] Morgan State University, United States of America
[m] University of California, Riverside, United States of America
[n] Oak Ridge National Laboratory, United States of America
[o] Smithsonian Environmental Research Center, United States of America
[p] Boston University, United States of America
[q] International Institute of Tropical Forestry, USDA Forest Service, United States of America
[r] Lawrence Berkeley National Lab, United States of America
[s] University of Colorado, Boulder, United States of America
[t] University of Western Ontario, Canada
[u] Columbia University and Lamont-Doherty Earth Observatory, United States of America
[v] University of Illinois Chicago, United States of America
[w] Carnegie Institution for Science, United States of America
[x] Earth from Space Institute, Universities Space Research Association (USRA), United States of America
[y] University of California Los Angeles, United States of America
[z] Colorado State University, United States of America
[aa] University of California Santa Barbara, United States of America
[ab] Spark Climate Solutions, United States of America
[ac] U.S. Geological Survey, United States of America
[ad] Japan Aerospace Exploration Agency (JAXA), Japan
[ae] Department of Physics, University of Toronto, Canada

* Corresponding author.
E-mail address: nicholas.c.parazoo@jpl.nasa.gov (N.C. Parazoo).
[1] Co-first author

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A B S T R A C T

Greenhouse gas (GHG) emissions continue to grow, while natural carbon reservoirs are becoming increasingly vulnerable to anthropogenic pressures, climate extremes, and disturbance. These changes are impacting humans, ecosystems, and natural resources worldwide. Tracking and mitigating GHG emissions require a pivot to operational monitoring of regional carbon flux and stock changes. The current GHG observing system is addressing needs at two distinct scales: 1) Local scale (< 1 km), related to anthropogenic point source emissions, and 2) global scales (> 1000 km), related to land and ocean carbon sinks. More focus on intermediate (10–1000 km) scales is needed to more effectively monitor progress in reducing carbon emissions, enhancing removals, and maintaining sinks.Representatives from carbon cycle biomass and flux communities across United States government agencies and academic institutions met in September 2024 to discuss the rationale and scientific context for more effectively implementing an operational system for GHG monitoring in support of urban and national carbon management needs. To guide development of this system, we propose a multi-tiered global spaceborne observing framework for carbon flux and stock, prioritizing: 1) frequent GHG partial columns for carbon emissions and removals; 2) continuous time series and data fusion of biomass from Lidar and Synthetic Aperture Radar (SAR) for carbon stocks, and 3) expanded coverage of tropical, high latitude, and oceanic regions to monitor carbon cycle tipping points and feedbacks. This system should be complemented by expanded surface and airborne networks for oceanic and terrestrial/aquatic ecosystems for calibration, ground truthing, and study of under-sampled regions.

Plain language summary: The rate of growth in global CO_2 emissions has been in decline over the last decade following efforts to enact climate policy, shift to clean energy, and mitigate leaks from oil and gas facilities. This is good progress, but with emissions of both CO_2 and methane (CH_4) on the rise, time is running out to meet temperature targets. Spaceborne greenhouse gas (GHG) observations can help monitor emissions/removals and track progress at the urban- to country- level, but currently lack the frequency, coverage, and precision to do so. Representatives from the carbon cycle community convened in September 2024 to discuss viable options for addressing these limitations. We recommend a unified GHG observing system leveraging frequent (daily) sampling and vertical profiles of atmospheric GHGs to more accurately track carbon gains and losses, and harmonized maps of biomass to track growth, recovery, and disturbance. Expanded coverage of climate sensitive tropical, polar, and ocean regions is needed to monitor unexpected changes in the natural carbon cycle. Complementary data from airplanes and surface networks is needed to fill observational and science gaps. This system should prioritize timely delivery of carbon flux and stock information to support carbon management efforts.

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1. Introduction: increasing demand for flux information at multiple scales

In 1994, 198 countries signed the United Nations Framework Convention on Climate Change (UNFCCC). The objective of this treaty was to stabilize atmospheric greenhouse gas (GHG) concentrations at levels "*that would prevent dangerous anthropogenic interference in the climate system*." Thanks to international efforts to enact climate policy, advance technology, shift from coal to gas, and expand the use of renewable energies, the growth in CO_2 emissions from human activities has declined from peak values of 3% in the 2000s to an average rate of 0.6% per year over the last decade (Friedlingstein et al., 2024). Likewise, significant progress is being made to detect, quantify, and mitigate GHG leaks from oil and gas facilities (e.g., Cusworth et al., 2022), which have contributed to accelerating growth in CH_4 emissions. Though we are still far from the sharp and sustained reductions needed to meet temperature targets, these efforts represent significant progress and underscore the potential for more targeted and sustained carbon management, representing the collective effort aimed at mitigation, i.e., reducing GHG emissions, and adaptation, to prepare for and address the consequences of climate change on land and ocean resources.

The growing Earth Observation (EO) record has been tracking global progress towards GHG mitigation goals since the 1950s and is an essential component of global, multi-scale carbon management efforts. GHG monitoring was pioneered first by the Scripps CO_2 Program, and then complemented by international networks from the National Oceanic and Atmospheric Administration (NOAA), the European Union (EU) Integrated Carbon Observation System (ICOS), and the World Meteorological Organization (WMO) Global Atmosphere Watch Programme (GAW) through high precision analysis of CO_2 mole fractions at remote background locations. These monitoring efforts are ongoing but have since been augmented by space-based GHG sensors, which are refining our understanding of fugitive emissions from intense point sources and net exchanges of over large land and ocean regions. At the same time, spaceborne biomass observing systems have been monitoring changes in carbon storage in vegetation for the past two decades. These observations provide a critical piece of information for interpreting terrestrial GHG fluxes. Continued growth and development of GHG flux and biomass observing systems has potential to more directly inform carbon management efforts at scales between point source emissions and large scale exchanges.

To provide scientific guidance for the next Decadal Survey (DS) on where, over which timescales, and how multi-tiered GHG monitoring activities should best observe the Earth System into the future, and how to address remaining scientific and information gaps and meet carbon management needs of national and international stakeholders, representatives from the carbon cycle biomass and flux communities across government agencies and academic institutions in the United States convened for a three-day workshop in September 2024. Recognizing that GHG observations on their own are insufficient for informing carbon management, workshop participants first discussed the state of knowledge, gaps in understanding, and opportunities for improvement in three areas needed to implement an operational system for GHG monitoring and prediction: 1) scientific knowledge, 2) information technology, and 3) Earth System feedbacks. Participants then discussed opportunities for progress including potential ways to address gaps that exist with respect to data, knowledge, and stakeholder engagement, and identification of viable spaceborne technologies that could better support the needs of urban, national, and international stakeholders. Despite progress at local and global scales from point source imagers and area flux mappers, respectively, there remains a significant gap in the ability of the current generation of space-based sensors to monitor weaker, spatially-distributed emissions and removals in larger urban and non-urban areas. Our discussions therefore focused on urban and national needs, primarily in the U.S. but with globally relevant implications, that can be addressed at intermediate scales (10–1000 km) through novel application and combination of existing technologies.

Based on these discussions, we offer a vision for implementation of an actionable system leveraging (a) partial column GHG data and (b) integration of top-down/bottom-up analyses to link new and existing carbon cycle information across scales. The first portion of the paper (Sections 2–4) addresses the programmatic landscape by providing background on recent historical efforts to support carbon management through GHG monitoring (Section 2), offering some reasoning to transition from science-focused GHG monitoring to a more coordinated carbon management system that blends together research- and operational- oriented efforts (Section 3), and summarizing opportunities to advance this system through the Decadal Survey process (Section 4). The middle portion (Sections 5–7) sets the stage for our recommendations for a next generation carbon management system, by first detailing current scientific knowledge and gaps (Section 5), summarizing advances in information systems to more effectively leverage Earth observations (Section 6), and summarizing the status and limitations of current and planned carbon cycle flux and biomass observations

Table 1
Spatial and temporal scale requirements for carbon management. The largest and smallest scales (continental and local) are currently, or will be partially addressed by the EO Program of Record. The intermediate scales (10–1000 km; weekly to decadal), representing regions of significant scientific uncertainty, are currently poorly observed. Our observing system recommendations focus on addressing carbon management needs at these scales.

Region	Spatial Scale	Temporal Scale	Description	Uncertainty	Observation Sampling Requirement	Flux and Precision Requirement
Continental	> 1000 km	Annual—Decadal	Sum of anthropogenic emissions and natural flux in global ocean basins and continents	Time-mean flux over land or ocean; Partitioning between regions (e.g., tropics vs. extra-tropics); Long term response to changing forcing and feedbacks	Continuous global monitoring; Targeted monitoring of key land and ocean regions (tropics, Arctic, Southern Ocean); Regular updates to global carbon budget (~annual)	~100–500 km to capture sub-continental spatial patterns and processes; Precision <0.25%; Accuracy <0.1%
Country	100—1000 km	Annual—Decadal	Balanced contributions from natural and anthropogenic GHG sectors	Continuous monitoring of trends to verify NDCs; Separation of natural (urban and non-urban land and aquatic systems) and anthropogenic (fossil emissions, landfills, agriculture) sectors	Sectoral attribution requires complementary data beyond primary GHG data (e.g., isotopes, OCS, NO_2) to disentangle sources	~10–50 km to capture sub-country spatial and temporal patterns; Precision <0.25%; Accuracy <0.1%
Urban	10—100 km	Subseasonal—Decadal	Emissions and removals across urban forests, managed and working lands, and fossil fuel sectors	Spatially-explicit mapping and separation of natural and anthropogenic sectors to determine the effectiveness of climate action across urban gradients	Verification of emissions reductions requires (1) continuous monitoring and (2) sectoral attribution using complementary data	~0.1–1 km to capture mixed spatial patterns; Precision <0.25%; Accuracy <0.1%
Ecosystem	5—50 km	Weekly to Decadal	Disturbance, including extreme events, climate anomalies, infestation, and land-use change	Detection and tracking of carbon source and sink trends and disturbance drivers, onset, and recovery	Monitoring of diffuse carbon fluxes; Sudden biomass and flux change detection; Deployment of rapid response systems for ecosystem monitoring, mitigation, and assessment	~1 km to capture landscape gradients; Precision <0.25%; Accuracy <0.1%
Local	1—10 km	Weekly to Decadal	Single GHG mitigation sector, such as fugitive emissions from oil/gas facilities and landfills, and removals from carbon dioxide removal efforts	Mitigation sectors are typically poorly regulated and inadequately monitored, which can lead to overestimation of impact and over-crediting in forest conservation and restoration projects	Monitoring of local scale mitigation efforts requires focused, long-term continuous monitoring of biomass and carbon flux	~0.1–1 km, to resolve individual projects; Precision <0.25%; Accuracy <0.1%

(Section 7). The final portion (Sections 8–10) summarizes requirements and best-practice recommendations from this workshop for implementation of an operational, global-scale GHG system, including recommendations for hierarchical data collection (Section 8) and a decision support framework leveraging information systems discussed in Section 6 to linking actionable knowledge to observing systems (Section 9), and opportunities for Earth science to action coordination (Section 10). Section 11 offers concluding remarks and summary of recommendations for a next generation multi-scale carbon management system.

2. Monitoring GHGs to support carbon management

National inventories of anthropogenic sources and removals of GHGs have been developed using best-practice methodologies accepted by the Intergovernmental Panel on Climate Change (IPCC, 2006). These methods are based on “bottom-up” inventories, compiled from a statistical analysis of anthropogenic and land emissions and removals reported from sources in specific sectors and categories. The 2019 update to the IPCC 2006 guidelines for inventory development reinforces this bottom-up approach, but also acknowledges the value of “top-down” approaches for quality control and assurance (Intergovernmental Panel on Climate Change (IPCC), 2019). Top-down methods provide an independent approach to bottom-up methods in their use of atmospheric measurements of GHG concentrations in conjunction with transport models and inverse (i.e., data assimilation) methods to infer net GHG emissions and removals and their spatial distribution.

In an effort to further support World Meteorological Congress (WMO) Members in mitigation actions, the WMO established a new global GHG monitoring initiative in 2023 called the WMO Global Greenhouse Gas Watch (G3W, https://wmo.int/activities/global-greenhouse-gas-watch-g3w). The primary goal of the WMO G3W is to coordinate and standardize ground, air and spaceborne observations, data formats, and assimilation approaches to provide consistent, global fields of net GHG fluxes. This effort was developed in a close collaboration between WMO and partner organizations concerned with GHGs and the carbon cycle.

In the U.S., national efforts such as the U.S. Greenhouse Gas Center play an important coordination role of Federal GHG information to support stakeholders from local-to-international scales. The GHG Center is already hosting societally-relevant GHG data, e.g., Global Carbon Stocktake (GST) carbon fluxes based upon top-down approaches, and forging new techniques to integrate multi-scale data from surface, airborne, and spaceborne platforms, e.g., NOAA/NASA AirMAPS campaigns. These data in turn are beginning to impact stakeholders and expand the suite of carbon information available to them. Efforts such as the GHG Center benefit from integrated GHG observing systems to monitor and facilitate the transition to decarbonization, focusing on coordination across federal and non-federal, domestic, and international entities to integrate and distribute actionable GHG data.

An operational system for GHG monitoring should reflect diverse public and policy relevant needs, as discussed below. A great example of this is the Copernicus program, which is managed by the European Union. Copernicus is taking steps to address operational GHG needs through future missions such as the Copernicus Anthropogenic Carbon Dioxide Monitoring (CO2M) mission, which will monitor global human emissions and whether or not mitigation efforts are on track.

3. Rationale for an operational system for GHG monitoring

Coordinated, national and international operational GHG monitoring systems leveraging bottom-up inventories and top-down inferences can more accurately support Nationally Determined Contributions (NDCs), carbon market tracking and other near- and long-term carbon management efforts. However, current monitoring systems are ad hoc, based primarily on inquiry-driven scientific research, and underutilize the full suite of EO technologies. This stresses the need for a Program of Record (PoR), comprising long-term observables ideally supported by sustained funding and defined standards for continuously collecting, processing, and archiving EO data to ensure uninterrupted, consistent datasets. Carbon flux monitoring and attribution has diverse spatial and temporal scale requirements depending on the process and mitigation action (Table 1). Spatial scales span local, ecosystem, urban, sub-national, national, and continental domains. Temporal scales span weekly, subseasonal, annual, and decadal domains. Examples include early warning and rapid response to carbon emissions resulting from disasters and disturbances (e.g., assessment of impacts to carbon offset projects and national inventory reporting), evaluating the effectiveness of national and sub-national emissions reductions efforts (e.g., improvements in efficiency of energy consumption and waste water treatment), evaluating and improving urban and rural land-use planning (e.g., providing data-driven insights into emission hotspots and green infrastructure development), offering science-based solutions for resource management decisions in the context of climate mitigation via land management, nature based solutions, post-disturbance restoration/recovery, and facilitation of ecosystem adaptation, and tracking tipping

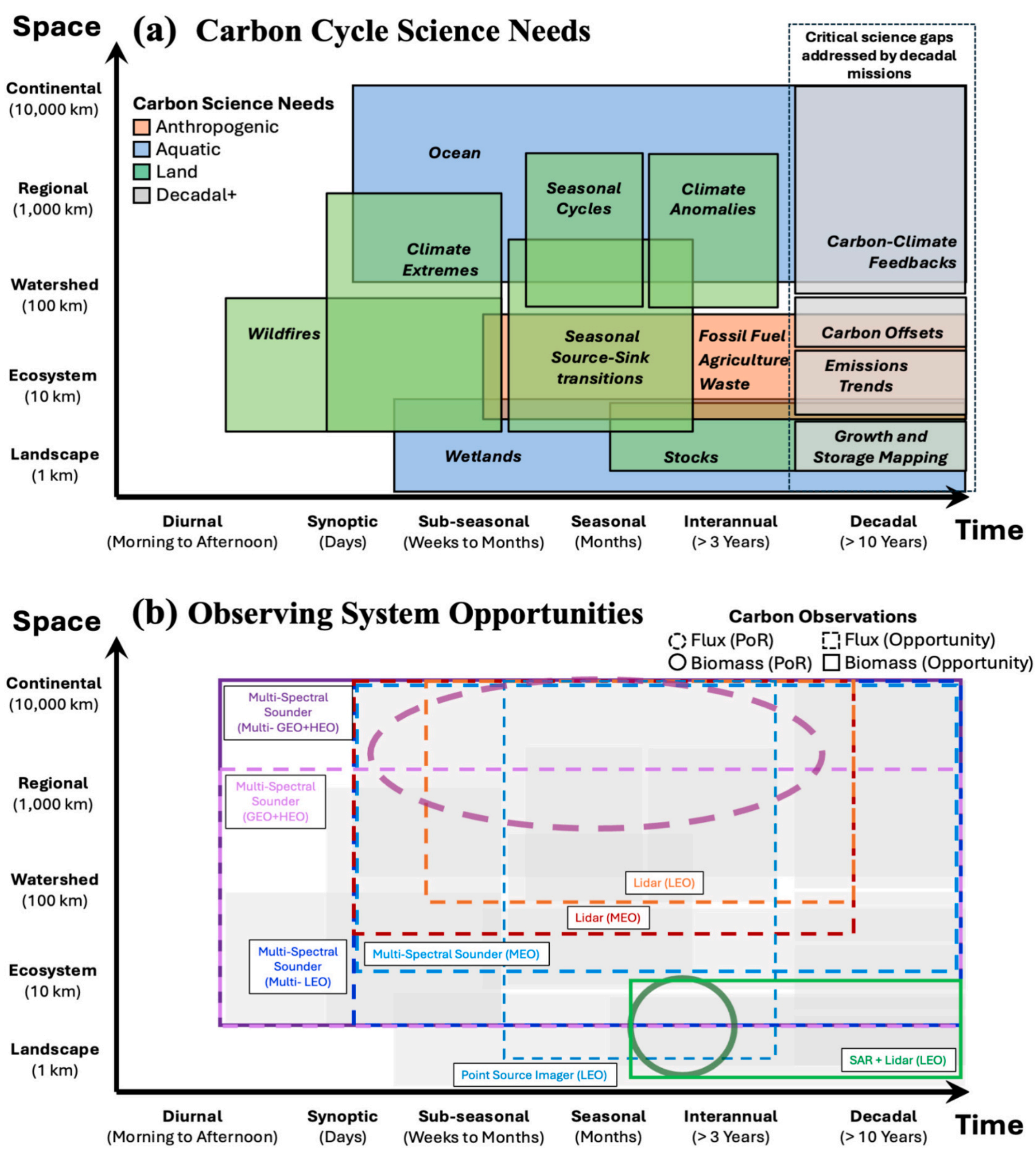

Fig. 1. Carbon cycle science and management needs and corresponding observing system gaps and opportunities. (a) Summary of diverse carbon cycle science needs spanning multiple time (x-axis) and space (y-axis) scales across land (green shading), ocean (blue shading), and anthropogenic (orange shading) sectors, adopted from Parazoo et al. (2025). (b) The current and planned spaceborne observing system for GHG flux (dashed circle) and biomass (solid circle) indicates coverage of local (< 1 km) and continental (> 1000 km) scales. Critical gaps remain at intermediate spatial scales (10–1000 km) and over longer time scales (grey shading) that require multi-decadal observing system architectures. Several opportunities to expand upon the GHG Program of Record to address critical gaps (dashed and solid boxes) are presented. Observing systems include the use of Lidar, point-source imagers, and multi-spectral sounders in low earth orbit (LEO), medium earth orbit (MEO), geosynchronous orbit (GEO), and highly-elliptical orbit (HEO) are presented. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

points and feedbacks in high carbon storage areas such as the northern high latitude Arctic-Boreal region (denoted Arctic hereafter for simplicity), tropics, and oceans (e.g., to track sudden and/or long term emissions with potential to offset mitigation efforts). Importantly, GHG data joined with real-time climate management actions allows for improved quantitative and spatially-explicit understanding of how changes in land use and disturbance affect carbon storage, GHG emissions, and climate mitigation efforts on policy-relevant time scales, providing opportunities for iterative learning and decision-making. High GHG precision ($< 0.25\%$) and accuracy ($< 0.1\%$) across regions and scales will be necessary to ensure high and unbiased sensitivity to weaker fluxes from natural processes (e.g., Miller et al., 2020; Chevallier et al., 2023).

Despite increasing availability of EO data to fuel scientific research, its full potential to inform measurable and actionable carbon management at local-to-global scales remains underutilized. The ability of coordinated carbon management efforts to benefit from a global GHG observing system requires a paradigm shift in how EO data is collected, shared, integrated, and operationalized. Implementation of an operational system leveraging models and observations has historical precedence in numerical weather prediction (NWP). The U.S. began operational NWP in 1955, five years after the first computer-produced weather forecast was generated. This early weather forecast system used a simple three-layer model for the Northern Hemisphere. Over the past decades, following growth in computing resources, improved scientific understanding, and the development of machine learning (ML) tools, NWP has experienced substantial gains in skill and performance (Bauer et al., 2015). The implementation of an operational system, with models capable of assimilating observations using similar methods and mathematical frameworks as GHG inverse methods, was one of the key advances behind these gains. The assimilation of vast amounts of heterogeneously-distributed observational data has been made possible by the number of EO satellites launched since the 1980s. Assimilation of EO data has enabled better constraints for model initial conditions and the development of high-resolution global forecasts, ultimately leading to improved model predictions and quantification of forecast uncertainty at regional-to-global scales (Park and Xu, 2013). Additionally, the ability to assimilate new types of observations facilitates improvements in process representation within weather models, better constraining their parameterization (Bauer et al., 2015). Critically, global coverage from satellite data has advanced NWP to the point that predictive skill is comparable in most parts of the world.

The successes of NWP can serve as a model for the development of an operational system for GHG monitoring and prediction. Operational weather prediction and carbon monitoring have similar technological requirements and potential benefits to society: both systems use similar mathematical and computational frameworks, reduce risk and improve quality of life through monitoring and prediction, and support improved, shared scientific understanding. NWP benefits society through its ability to both reduce risk and improve socioeconomic outcomes. The ability to forecast extreme weather events (e.g., flooding, drought, fires) informs response strategies that are critical to mitigating the loss of life and property, while the capacity to predict weather on a day-to-day operational basis (e.g., rain coverage and probability, temperature forecasts) guides daily personal, commercial, and management decisions such as activity planning, aviation, and crop harvest. Similarly, an operational system for GHG monitoring, focused on tracking changes in emissions and removals over time scales of months to years, could inform policy making, urban planning, regulation compliance, disaster and disturbance response, and other carbon management needs. Though the immediate usefulness of data is fundamentally different between NWP (daily) and GHG (months to years) monitoring, we stress that both systems serve as operational frameworks for informing action.

NWP benefits from the feedback loop between the operational system and discovery science. For example, NWP has both been improved by and supported better understanding of subgrid-scale processes (e.g., vertical transport, cloud microphysics, boundary layer dynamics) and atmospheric chemistry (e.g., aerosol impacts on radiation, cloud condensation nuclei). An operational system for GHG monitoring and prediction, informed by a multi-tiered global observing system, would support a similar feedback cycle by improving our understanding of the climate sensitivities, global carbon budgets, ecosystem resilience to disturbance, and carbon-climate feedbacks necessary to further advance operational systems in support of short- and long-term carbon management needs.

4. Decadal survey: GHG-specific earth science needs

The Decadal Survey process, led by National Academy for Sciences Engineering and Medicine (NASEM), is vital for planning future investments based on community inputs and anticipated observational needs and provides key recommendations for GHG measurements and monitoring. The most recent survey, in 2017, recommended a program that was implementable, balanced, and carefully considered to enable advances in Earth System science and applications from space with the resources that were stipulated to be available during the decade. A midterm assessment of progress towards implementing the 2017 Decadal Survey found that the increased availability and variety of EO data has resulted in an exponential growth of their use to advance science and applications, support operational decisions, and address a broad myriad of societal needs (National Academies of Sciences, Engineering, and Medicine, 2024). There was limited progress, however, towards implementing new missions recommended by the survey, due in part to the challenge in meeting the needs of the growing community of stakeholders impacted by climate change across public, private and philanthropic sectors (National Academies of Sciences, Engineering, and

Table 2
Key focus areas for observing system, science, and carbon management needs across the earth system. GHG focus areas span anthropogenic and natural sectors for fossil CO_2, biogenic and anthropogenic CH_4, and biogenic CO_2 exchange in the land and ocean.

Focus Area	Fossil CO_2	Anthropogenic and Biogenic CH_4	Land CO_2	Ocean CO_2	Complex GHG Feedbacks
Observing Need	Spaceborne monitoring and sectoral attribution of urban emissions	Improved sampling of natural sources, with a focus on tropical, high latitude, and wetland regions	Storage and exchange of carbon in forests	Improved monitoring of the global ocean, with a focus on the Southern Ocean	Sustained, long- term monitoring of land and ocean feedbacks
Science Need	Disaggregation of urban emissions for process attribution, Reduced uncertainty in fossil carbon will enable more accurate estimates of the land budget	Attribution of growth in global CH_4 concentration	Mapping of forest carbon budget for improved understanding of climate sensitivity	Observing and mapping ocean carbon fluxes for more accurate ocean/land sink partitioning and detection of ocean feedbacks	Improved understanding and quantification of climate sensitivity
Carbon Management Need	Fossil emissions tracking and mitigation	Detecting and mitigating anthropogenic emissions	Forest management, national reporting, monitoring of disturbance impacts	No immediate need met, though improved space/time mapping could support mCDR	Determine urgency for near-term carbon management efforts

Medicine, 2024).

Moving forward, it is recommended that the next survey (2027–2028) should 1) involve a wider community of stakeholders earlier to better understand both their short- and long-term needs, 2) more directly involve the modeling community, and 3) develop strategies for observational continuity to support long term monitoring. The 2028 Decadal Survey should focus broadly on meeting the shifting carbon management needs of today and the future. This requires sustained and operational GHG monitoring to mitigate emissions and track feedbacks, including production and delivery of timely and policy-relevant information on carbon emissions, removals, and stocks to national and international stakeholders. New spaceborne strategies will be needed to more accurately pinpoint spatially distributed emissions and removals in larger urban and non-urban areas and better complement the growing amount of information from the fleet of point source imagers. The 2028 Decadal Survey should also consider opportunities to more fully exploit the wealth of current and planned EO data into GHG monitoring activities, as well as opportunities to address observational needs of the 2030–2050 world, driven by amplified carbon-climate feedbacks under a rapidly-changing Earth System and shifts in the sign and magnitude of feedbacks as climate stabilizes with decreasing emissions.

5. Advances and gaps in scientific knowledge

The Earth System consists of a range of natural and anthropogenic processes operating at various spatial and temporal scales in the land, ocean, and atmosphere which continuously store and transfer carbon within and across pools (Fig. 1). The fundamental processes of photosynthesis and respiration governing global ecosystem metabolism and the exchange of carbon between the land, ocean, and atmosphere are generally well understood at the scale of individual plants and soil samples due to decades of laboratory- and field-based research. However, the range of responses of these processes to changes in atmospheric CO_2 and climate forcing across global land and ocean ecosystems remain poorly understood. For the same reason, our ability to detect and quantify anthropogenic emissions and emissions change, and disentangle these changes from natural processes, remains limited, despite a strong understanding of combustion processes associated with fossil fuel CO_2 emissions ($FFCO_2$). Inland aquatic ecosystems have not played a large role in previous global carbon budget assessments but have been given increased scrutiny with recent acceleration of global CH_4 concentrations. The following sub-sections summarize broad advances and gaps in scientific knowledge across anthropogenic and land GHG sectors, along with identifying potential future feedbacks. For each subsection, we then identify key observational gaps (summarized in Table 2) to help focus our recommendations for a spaceborne observing system meeting multiple scientific and carbon management needs.

5.1. Fossil CO_2

$FFCO_2$ is a major input of carbon (C) to the atmosphere. Since the industrial revolution, humans have added 480 Pg C to the atmosphere by extracting and burning fossil fuels, such as coal, oil, and gas (Hefner and Marland, 2023). $FFCO_2$ is historically defined as the sum of CO_2 emissions from fossil fuels, gas flares, and cement production (e.g., Marland and Rotty, 1984; Andres et al., 2012). $FFCO_2$, like other emissions, is often estimated using an activity-data (bottom-up) approach (Marland and Rotty, 1984). Global and national annual $FFCO_2$ emissions are thought to be robustly estimated from global and country fuel consumption data (uncertainties of ~10% for global; ~5% for countries with good statistical data collection systems; 20% or more for countries with poor statistical data collection systems) (Andres et al., 1996; Marland, 2008; Andres et al., 2014). In general, fossil emissions have declined across the group of developed countries of the Organization for Economic Co-operation and Development (OECD) over the period 2013–2022, while increasing emissions from non-OECD countries have been the driver for the $FFCO_2$ increase in recent years (Friedlingstein et al., 2023).

Sectoral level attribution of emissions reductions requires disaggregation of national level emissions to finer temporal and spatial scales. Sub-national level (state/province/prefecture) emission estimates are available in some countries, such as in the U.S. and China. In global and regional gridded datasets, sub-national and sub-annual emissions are disaggregated using spatial and temporal data that approximate activity level changes (Andres et al., 1996, 2011; Oda and Maksyutov, 2011; Oda et al., 2018). Because of the many assumptions required to disaggregate emissions, sub-national and sub-annual emissions are generally more uncertain compared to national estimates as emissions become decorrelated from activity levels (Hogue et al., 2016; Oda et al., 2019, 2021, 2023).

Top-down (atmospheric data-based) approaches are also needed to help detect and correct biases. However, large scale CO_2 inverse estimates often assume $FFCO_2$ as known (Gurney et al., 2005; Wang et al., 2020; Oda et al., 2023). Due to mass balance requirements, this assumption raises the risk of uncorrected $FFCO_2$ biases being aliased to other regions and processes. Dense urban data have increasingly become available to study human emissions, including $FFCO_2$ from major cities (Duren and Miller, 2012). A U.S. study uniquely demonstrated the use of ^{14}C for evaluating country level $FFCO_2$ using inverse modeling (Basu et al., 2020). While these data provide important constraints on the major components of subnational emissions and their spatial gradients and temporal variability, spaceborne GHG monitoring is needed for more complete coverage at national and international levels (Kiel et al., 2021). Spaceborne monitoring and sectoral attribution of urban $FFCO_2$ emissions have significant potential to reduce carbon budget uncertainties and to directly inform carbon management efforts and thus represent a key focus area for our recommendations.

5.2. Biogenic and anthropogenic methane

After a period of low atmospheric growth in the early 2000s, methane began increasing again after 2006. Methane growth has accelerated in recent years with some years registering the highest growth rates since global network records began in 1985 (Lan et al., 2022). The cause(s) of the recent atmospheric growth is not currently understood, but could include growth in anthropogenic emissions from fossil fuel production and agriculture and waste, and increases from natural sources, possibly in response to climate change (Saunois et al., 2024). Due to its short lifespan (half life ~10 years), the global warming potential (GWP) of CH_4 is very high when looking at short time scales. Reducing methane emissions in the near term thus represents an important GHG mitigation opportunity in terms of reducing GWP and keeping global temperatures below their targets (Shindell et al., 2021).

Understanding how individual sources of methane are changing over time is hampered by 1) uncertainties in chemical removal in the atmosphere by hydroxyl radical (OH) (Turner et al., 2017; Rigby et al., 2017), 2) the limited space-time resolution of anthropogenic and natural emission datasets, and 3) poor observational coverage of CH_4 concentration in the tropics, Arctic, and in regions with wetlands. The distribution and trends of OH are more difficult to quantify using current observational approaches such as methyl chloroform (MCL), which is reaching undetectable levels due to its Montreal Protocol phase-out. Further research is needed to identify other potential proxies and observational constraints on OH, such as the deuterium isotope of methane (CH_3D), ^{14}CO, and possibly other halogenated compounds. The ability to quantify methane emissions is further complicated by fugitive or incidental processes, such as leaks in pipelines, degradation of organic matter in landfills, and the digestive processes of ruminants.

Likewise, the distribution of natural sources remains highly uncertain. Wetlands provide a spatially heterogeneous source of methane (Nesser et al., 2024). Estimates based on satellite inundation products suggest that emissions from wetlands and inland waters have been relatively constant or possibly slightly declining over past decades (Zhang et al., 2021). In contrast, methane emission models that predict wetland extent show small increases in CH_4 of 6–7 Tg CH_4 yr^{-1} driven mainly by increasing temperature (Zhang et al., 2025). Global network observations of $^{13}CH_4$ indicate that growth in atmospheric methane is driven mainly by microbial processes (i.e., in wetlands and inland waters, agriculture, and waste) (Michel et al., 2024). More detailed and accurate source inventories and complementary information of the spatial distribution of wetlands, inland waters, and CH_4 sampling are all needed to improve source attribution. Given uncertainty in natural CH_4 emissions and the global scope of the problem, we include improved sampling of natural sources from wetlands in remote tropical and arctic regions in our recommendations.

5.3. Terrestrial carbon

Land model ensembles from The Global Carbon Project (GCP) estimate that terrestrial processes absorbed ~3.2 ± 0.9 Pg C yr^{-1} on average from 2013 to 2022 (Friedlingstein et al., 2024), with the primary driver being sequestration by vegetation in forests (Bultan et al., 2022; Grassi et al., 2023). At the same time, carbon emissions from land use, land-use change, and forestry (primarily deforestation) total ~ 1.1 ± 0.7 Pg C yr^{-1}. Strengthening the net land sink involves both curbing deforestation and degradation efforts and bolstering sequestration through management and mitigation activities such as restoration. Many processes influence the global land flux, including emissions from disturbance (fire, drought, pests, storms), anthropogenic emissions from deforestation and degradation, removals for food and fiber production, and removals from vegetation regrowth and afforestation (Harris et al., 2021; Xu et al., 2021). Attribution of top-down observations of net flux from land is challenging, and while EO data have increased our understanding of some fluxes (e.g., from the passive optical record to monitor land cover and land-use change), considerable uncertainties remain in the above- and below-ground carbon fluxes, particularly from disturbance and regrowth. The trends in land fluxes, as well as the location and magnitude of the land sink, have been the subject of scientific scrutiny in recent years, highlighting the uncertain roles of different carbon pools and geographic discrepancies across tropical, temperate, and boreal landscapes (Xu et al., 2021; Fan et al., 2023; Luyssaert et al., 2021; Sitch et al., 2024). A major challenge lies in resolving discrepancies in national inventory-based estimates of land carbon stocks and fluxes with EO-based estimates, largely due to differences in what is considered managed land for reporting (Grassi et al., 2023). Uncertainties in land fluxes are the largest (by percentage) of any carbon pool (Friedlingstein et al., 2024), highlighting the complexity of the land system and the challenge at hand. Future changes due to several land carbon cycle feedbacks (e.g. shifting growth rates with warming) increase the complexity and strengthen the need for a long-term monitoring system (*see Section 5.5*). While the land system is ecologically diverse, the storage and diffuse exchange of CO_2 in forests account for most current carbon stocks and fluxes (Pan et al., 2024) and are thus the focus of our recommendations.

5.4. Ocean carbon

Based on GCP ocean models and data-based products, the ocean has absorbed additional carbon equivalent to 37% of cumulative fossil fuel emissions since 1850, and in 2013–2022 2.8 ± 0.4 Pg C yr^{-1}; and thus has significantly mitigated climate change (Friedlingstein et al., 2024). Though globally-integrated estimates of the ocean carbon sink agree to within 0.6 Pg C yr^{-1} in 2022, estimates differ to a much larger extent at local-to-regional scales (Fay and McKinley, 2021; Crisp et al., 2022; McKinley et al., 2026). This is because air-sea CO_2 fluxes are dominated by large-compensating fluxes due to natural processes, including biological productivity/export and circulation, resulting in high variability in both space and time (Carroll et al., 2020, 2022; Crisp et al., 2022; Gruber et al., 2023; Fay et al., 2024). Additionally, forced and internal climate variability drive significant interannual anomalies (McKinley et al., 2017; Crisp et al., 2022; Gruber et al., 2023; Fay et al., 2023). Ocean uptake of anthropogenic carbon is superimposed on this dynamic background. Due to the strong forcing from growing atmospheric pCO_2, spatially integrating fluxes at the global scale sums compensating regional differences, leading to more consistent global values (McKinley et al., 2020). The dynamic background on top of which the anthropogenic fluxes occur challenges the detection of change in the sinks in response to the changing atmospheric pCO_2 growth rate (Fay et al., 2024), for example as associated with the COVID19 pandemic (Lovenduski et al., 2021b).

Future progress to better constrain the global ocean carbon sink will require improvements to models, and more extensive collection of high-quality carbon data across the global ocean including the Southern Ocean (Gloege et al., 2021; Hauck et al., 2023; Heimdal and McKinley, 2024). Reduced uncertainty in the globally-integrated ocean carbon sink would lead to improved capacity to constrain the land carbon sink, and thus to monitor the global carbon cycle (Peters et al., 2017). Experimental studies have shown that the more-precise measurements of CO2 concentration over the ocean, including spaceborne measurements of reflected light (e.g., from the solar glint spot) provide additional information on land and ocean fluxes and flux error reductions (Feng et al., 2009; Baker et al., 2010). Our observing system recommendations focus on improved high-precision monitoring of the global ocean, with specific focus on the Southern Ocean in support of 1) improving quantification of the mean state and variability of the ocean sink, 2) increased capacity to detect ocean feedbacks, and 3) an improved constraint for the land carbon budget.

5.5. Increasingly complex feedbacks

The relationship between the carbon cycle and climate depends strongly on Earth System feedbacks. Our current understanding of carbon-climate feedbacks is based on accelerating emissions, in which rising atmospheric CO_2 levels create disequilibrium with the natural environment. Nature responds to this perturbation by 1) increasing the uptake of CO_2 from the atmosphere and 2) storing carbon in biomass, soils, and the oceans. The magnitude and rate of growth of these land and ocean carbon sinks depends on the sensitivity to rising temperature. The combination of all carbon cycle, cloud, and aerosol feedbacks to carbon and climate has led to an approximately linear increase in global temperature to cumulative emissions, representing the Transient Climate Response to Emissions (TCRE, Jones and Friedlingstein, 2020). However, the long-term temperature response to emissions is uncertain, depending on 1) the timescale to exhaust remaining carbon budget through emissions and feedbacks and 2) magnitude of climate sensitivity (Schimel and Carroll, 2024), estimated to be up 8 °C with a doubling of atmospheric CO_2 over the geological record (Judd et al., 2024).

Earth System feedbacks that may result from slowed or net negative emissions are less well understood. When atmospheric CO_2 levels rise at a slower rate or begin to fall as a result of intentional or unintentional emissions reductions, the land and ocean slow their rate of carbon absorption (Lovenduski et al., 2021a). However, the warming response to the emissions reductions (carbon-climate feedback) may operate on a different timescale than that of the carbon-concentration feedback (Koven et al., 2023), complicating our understanding of the net feedback. Therefore, future projections of the climate response to human and natural CO_2 forcing are critically dependent on continued tracking and understanding of historical, modern, and future climate sensitivity, and well-assessed impacts of carbon management that include mitigation, adaptation, restoration, and technology-based removals. We must therefore also consider the need for sustained, long term monitoring of land and ocean feedbacks under changing emissions.

6. Advances in top-down and bottom-up information

The ability to reliably use a GHG observing system to move science and decision-support forward required the use of advanced models, data assimilation, and ML methods. Here, we briefly summarize these methods and provide focused recommendations for integrating GHG observing system elements.

6.1. Inversion modeling

Inverse analyses are the primary tool for using atmospheric GHG observations to improve estimates of net surface-atmosphere fluxes (e.g., Byrne et al., 2023; Qu et al., 2021). These analyses quantify the fluxes that best explain the observed quantities by fitting the data to simulated observations from models, often regularized by an initial flux estimate (i.e., a prior) generated by inventories or process-based models (Rodgers, 2000). Quantifying net fluxes at high spatial and temporal resolutions is important for improving our scientific understanding and assessing the efficacy of the carbon cycle, along with facilitating mitigation efforts. However, the spatial, temporal, and sectoral resolution at which these methods can reliably quantify fluxes depends on 1) the accuracy, precision, and quantity of observational data and 2) scientific understanding of the underlying processes driving spatio-temporal variability in the observed data.

With current data and scientific understanding, typical global inversions relying on global GHG mappers quantify net CO_2 fluxes at relatively coarse spatial (~1000s km^2 globally and higher resolution regionally) and temporal (weeks to months) scales (Byrne et al., 2023). Methane emissions are often optimized at finer spatial resolutions (~100 s km^2 globally and higher resolution regionally) and similar temporal scales (Qu et al., 2021; Estrada et al., 2024). Due to computational cost, these analyses rarely quantify the uncertainty of the net fluxes (Jacob et al., 2016). Current efforts are focused on 1) leveraging multi-tiered observations to increase spatiotemporal resolution and quality of the underlying models used for the initial flux estimates (e.g., Yang et al., 2022; Weir and Ott, 2024), and 2) improving uncertainty quantification with existing computational resources (Miller et al., 2020; Chevallier et al., 2023; Nesser et al., 2021). The GHG observing system should be sufficiently dense and have near-surface sensitivity to support increased spatiotemporal resolution in inverse analyses. To take advantage of increased local information, we recommend more formal integration of data assimilation and ML tools for improved downscaling and process level information (e.g., Dadheech et al., 2024; Chevallier et al., 2023).

6.2. Leveraging observations to constrain process-based models

Earth System Models (ESMs) are foundational tools for understanding the Earth's climate system and modeling interactions between key components — atmosphere, oceans, land, and cryosphere — that regulate the planet's energy, water, carbon, and nutrient cycles. Through these interactions, ESMs provide insights into natural and human-induced effects on climate, particularly in terms of carbon fluxes and storage (Braghiere et al., 2023). By using Dynamic Global Vegetation Models (DGVMs) for terrestrial sinks and global-ocean biogeochemical models (GOBMs), combined with observation-based data for ocean sinks, ESMs track and project carbon flows, contributing valuable context for climate change assessments. Observational data sources such atmospheric CO_2 inversions, SOCAT (Surface Ocean CO_2 Atlas, Bakker et al., 2016), and biomass (Bar-On et al., 2025) support model refinement by supplying extensive datasets on CO_2 fluxes and stocks, enhancing predictive accuracy for global carbon cycles (Friedlingstein et al., 2023) — continuation of these activities are essential.

Despite model advances, significant challenges persist in modeling carbon dynamics accurately (Fisher and Koven, 2020). Numerical ocean models are limited by coarsely-resolved physical and biogeochemical processes and parameterized processes, and exhibit significant mean-state errors at regional-to-global scales (Fay and McKinley, 2021), especially in data-scarce regions. These errors propagate into future projections, which requires further study to understand the underlying physical and biogeochemical drivers such as nutrient cycling, carbon allocation and storage, as well as ecosystem-specific dynamics that govern carbon-climate feedbacks and response or resilience to climate extremes (Fay and McKinley, 2021; Gloege et al., 2021; McKinley et al., 2023). Better understanding and representation of key processes in land and ocean systems are critical for achieving a holistic, responsive model framework that aids in projecting feedbacks, forecasting climate risks, and informing carbon management strategies.

Data assimilation is a critical step towards reconciling observation-based empirical knowledge with the mechanistic and physical principles of biospheric carbon cycling. The emergent dynamics and skill of bottom-up land modeling frameworks remain limited by the uncertain empirical parameterizations of many biospheric process controls (Rogers et al., 2017), their response to climate perturbations (Fisher and Koven, 2020; Blyth et al., 2021), and the historically sparse set of laboratory and field measurements used to parameterize model function. Remote sensing of the terrestrial and ocean biogeochemistry and carbon cycling is shifting the paradigm towards evidence-based observation-informed modeling, and yields a unique opportunity for the integration of a wide range of vegetation, carbon and water flux and stock observations and their covariance with environmental change into land and ocean models with uncertain parameters. Model-data integration frameworks provide a key capability for merging observational datasets with process knowledge to explicitly and quantitatively attribute the land carbon sink and its evolution in time into either 1) gross fluxes (photosynthesis, respiration, fires, solubility, and biological pump), and/or 2) state changes, such as changes in total biomass, dead organic carbon states, and ocean carbon. Data assimilation methods including state estimation (Carroll et al., 2020; Fox et al., 2022; Dokoohaki et al., 2022), parameter optimization and/or model state initialization within Carbon Cycle Data Assimilation Systems (CCDAS, MacBean et al., 2022; Bloom et al., 2020; Kern et al., 2024; Bultan et al., 2022), and model structure optimization (Reichstein et al., 2022) have demonstrated model improvement against independent evaluation metrics and reduced space-time uncertainties (Carroll et al., 2022) in support of improved monitoring and projection of the ocean carbon sink.

Two clear needs for constraining carbon pool trajectories for both the historical period and under future emissions scenarios, and their spatial partitioning, are long-term estimates of historical carbon stocks and a denser network of atmospheric GHG concentration (MacBean et al., 2022). Key to using an expanded GHG observing system to support model-data integration efforts will be 1) exploration of trade-offs between model complexity, predictive skill, and observational fidelity (Famiglietti et al., 2021); and 2) adopting and accelerating observation-inferred process model developments and benchmarking efforts. Addressing these needs is ultimately a key strategy towards enabling a sustained initiative towards inferring process-level knowledge from the synergistic EO record.

6.3. Leveraging machine learning to reconstruct observations

Networks of direct carbon flux measurements such as FLUXNET are rapidly growing and provide millions of observations (big data) across diverse environmental conditions (Pastorello et al., 2020; Delwiche et al., 2021). The richer and broader representative information content from the large amount of data from carbon flux networks is still largely untapped in bottom-up carbon cycle model development. ML unlocks the ability for models to learn non-linear and highly-conditional dependencies between big flux data and environmental covariates, which are applied in upscaling workflows with Monte Carlo simulation methods to generate globally-gridded flux products and uncertainty, e.g., FLUXCOM and X-BASE for carbon dioxide, and $UpCH_4$ for methane

(Tramontana et al., 2016; Jung et al., 2020; Nelson et al., 2024; McNicol et al., 2023).

We highlight several opportunities to improve the fidelity of ML-based products at regional and finer scales, and their interannual variability, for improved process attribution and to better inform inverse analyses. Improvements that occur due to increased coverage and resolution of flux and spectral predictor data may need to be tailored to specific ecosystem characteristics (e.g., drylands, Barnes et al., 2021). Ongoing growth of flux network data combined with upscaling efforts that integrate flux network data with EO will continue to fill gaps in global coverage, and we point to a particular need for methane observations across moisture gradients in the tropics (McNicol et al., 2023). Site-to-patch downscaling approaches can improve spatial attribution and functional response accuracy from existing data (Rey-Sanchez et al., 2022). Increasingly high-resolution remote sensing data (< 100 m), such as offered by existing biomass maps from ALOS and Lidar datasets (Yu et al., 2022; Santoro and Cartus, 2023), provides a vital link between site and landscape scales, where distinct ecosystems and associated phenologies require much smaller spatial resolution than possible with moderate-resolution instruments such as MODIS (Moon et al., 2022). Finally, advances in ML models primarily involve incorporation of knowledge-guided constraints (KGML), such as learning of additional process parameters and causal structures (Yuan et al., 2022). These techniques can improve the accuracy of GHG flux predictions and future warming sensitivity (Yuan et al., 2022), offering essential prior information for inverse analyses and process model evaluation.

Ocean-based methods, which rely on surface-ocean pCO_2 data and reconstructions from these datasets, leverage ML to extrapolate to global coverage as a function of sea-surface temperature (SST) and salinity (SSS), mixed layer depth (MLD), chlorophyll, and atmospheric χCO_2. Reconstruction-based methods also have uncertainties, particularly for low- and high-frequency variability, due to sparse data and differences in ML or other statistical approaches used to interpolate them (Gloege et al., 2021, Heimdal and McKinley, 2024, Gregor et al., 2024). There are substantial uncertainties in the closure between reconstructions and models (Friedlingstein et al., 2026). While numerical ocean models directly estimate the anthropogenic carbon sink, pCO_2-based products estimate the total carbon flux. To compare these, a pre-industrial outgassing of carbon of terrestrial origin must be taken into account. This flux is poorly constrained, with a range of globally-integrated estimates from 0.2 to 1.2 Pg C yr^{-1} (Lacroix et al., 2020; Kwon et al., 2021; Regnier et al., 2022; Liu et al., 2024) — the spatial distribution of this outgassing also remains largely unconstrained.

7. Earth observation program of record

The EO Program of Record is increasingly covering the major observable components of the global carbon cycle, including carbon stocks and fluxes in land, coastal, and ocean ecosystems, along with anthropogenic influences such as fossil fuel emissions and land-use change. Most of these components have been at least partially observed over the last 10 years, and will be observed in more detail over the next 5–7 years.

Multiple existing or planned satellite missions for terrestrial biomass (GEDI, ICESat-2, NISAR, ALOS-4, BIOMASS), ecosystem properties (Landsat-NEXT, LSTM, CHIME, SBG, ROSE-L, CIMR), ocean color (PACE, GLIMR), ocean properties (SWOT, Sentinel-3/6, CRISTAL), atmospheric GHG point source imagers (GHGSat, EMIT, MethaneSat, CarbonMapper), and area flux mappers (OCO-2/3, TROPOMI, GOSAT-2, SCIAMACHY, IASI, CO2M, MicroCarb, GOSAT-GW) will ensure ongoing regional-to-global coverage at multiple temporal and spatial resolutions (Committee on Earth Observing Satellites (CEOS), 2023, 2024).

The record also includes tracers for component GHG fluxes including carbonyl sulfide (IASI, ACE) and solar-induced chlorophyll fluorescence (SIF) (GOSAT/−2, OCO-2/3, TROPOMI, FLEX) for GPP (Sun et al., 2023; Cartwright et al., 2025), carbon monoxide (CO) for fire emissions (Sentinel-5, MTG, FireSat, TROPOMI), and nitrogen dioxide (NO_2) for fossil fuel emissions (TANGO, CO2M, TROPOMI) (Committee on Earth Observing Satellites (CEOS), 2024). The diversity of EO data is addressing the need to constrain the mean state of emissions, exchanges, and stocks, while the growing length of record is starting to address the need to track variability and long-term change.

Limitations in the spaceborne GHG and biomass record are summarized below. While this section focuses on space-based observations, we acknowledge the critical importance of in-situ observations for improved monitoring, data precision, temporal sampling under clear, cloudy, and smokey conditions, and advanced research opportunities. We provide recommendations for a complementary in-situ network in Section 8.

7.1. Limitations and opportunities in the spaceborne atmospheric GHG program of record

Global GHG mappers, including the recently launched GOSAT-GW

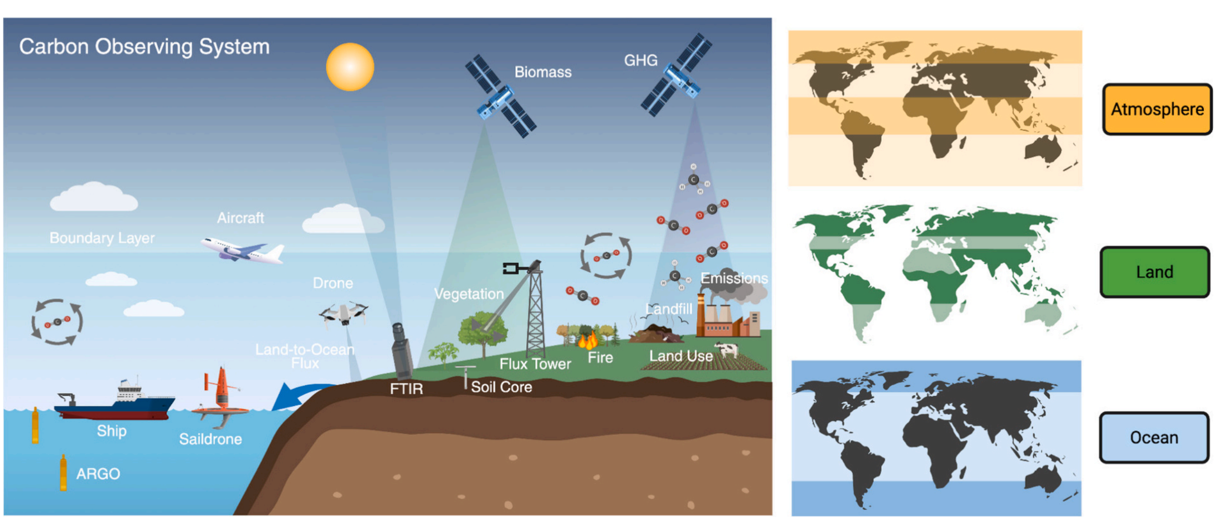

Fig. 2. Unified GHG observing system. [Left] Multi-tier carbon observing system showing atmosphere, land, and ocean components from Carroll et al. (2025a). [Right] Shaded horizontal bands show regions where critical EO and GHG data are needed. Land bands highlight regions of high carbon storage carbon cycle uncertainty. Atmospheric bands highlight areas of low observational coverage from space, due to clouds in the tropics and polar darkness and high solar angles in the Arctic. Ocean bands correspond to historically undersampled regions due to clouds, sea-ice cover, and polar darkness.

and the future CO2M constellation, will extend datasets from existing mappers (GOSAT/−2, OCO-2/3) with much higher spatial coverage. These sensors record high-resolution spectra of reflected sunlight in near infrared (NIR) wavelengths near 1.61 and 2.06 μm to constrain total column abundance of CO_2 and CH_4. They also collect spectra within the molecular oxygen (O_2) A-band, around 0.76 μm to account for dry air mass and to characterize cloud and aerosol scattering for column retrievals. These instruments require high accuracy ($< 0.25\%$) to reliably infer diffuse carbon fluxes (Committee on Earth Observing Satellites (CEOS), 2024; O'dell et al., 2018).

An important limitation of Global GHG mappers is the use of passive spectrometers to measure reflected sunlight. Their measurements work well in bright cloud free scenes, but their measurement densities and sensitivities fall off dramatically at high solar zenith angles, increasing cloud and aerosol optical depth, and low surface reflectivity, and they cannot measure in darkness. Many important GHG source regions are in cloudy regions, such as the tropics and subtropics and in the Arctic, which are dark from late fall to early spring. Despite improving retrieval accuracies, passive spectrometers lack the capabilities to determine GHG fluxes with needed resolution in the Arctic and tropics. Polar orbiting Lidar will be key in obtaining retrievals of GHGs with improved coverage, sampling, and precision to improve constraints on global, and regional GHG fluxes. Simulations performed for the NASA ASCENDS mission study (Kawa et al., 2018) and demonstrated by China's DQ-1 mission (Dai et al., 2023; Fan et al., 2024) demonstrate the dramatic increase in global coverage throughout all seasons and locations and even in the presence of scattered clouds and aerosols.

In spite of the growing space-based record, critical observational gaps still exist globally, and especially in key regions in the tropics, Arctic, and Southern and Arctic Oceans (Fig. 2). While our existing missions have provided proof-of-concept and the upcoming Program of Record will improve spatial and temporal sampling at global scale, the community recognizes the need for high resolution, cloud-free maps to address “data droughts” in tropical and high-latitude regions and the Southern Ocean (e.g., Frankenberg et al., 2024), given the significant role these regions play in the global carbon cycle. Polar orbiting Lidars provide enhanced global sampling but lack revisit frequency and mapping capability needed to detect and monitor transition seasons, climate extremes, and abrupt emissions. The polar and tropical regions are expected to have the largest carbon-climate feedbacks and lack coverage from both in-situ platforms and remote-sensing assets (Schimel and Carroll, 2024; Miner et al., 2022). Additionally, large swaths (~41%) of the terrestrial biosphere are water-limited, holding vast carbon stocks (Wang et al., 2022), and are characterized by high spatial heterogeneity, which yet require reliable techniques to partition vegetation from soil (Tucker et al., 2023; Feldman et al., 2024).

Likewise, the community acknowledges the significant progress being made by point source imagers to detect, quantify, and mitigate GHG leaks from oil and gas facilities (e.g., Cusworth et al., 2022), but recognizes the need for more targeted and long-term measurements of diffuse emissions and removals from both anthropogenic and natural processes that fall within intermediate spatial scales (10–1000 km), and beyond the temporal range (less than weekly, greater than 5–10 years), of global mappers and plume imagers (Fig. 1). These processes include anthropogenic-driven emissions from urban areas and landfills (and other microbial related processes) (Nesser et al., 2024), and removals by managed ecosystems within the Agriculture, Forestry and Other Land Use (AFOLU) sector (IPCC, 2022). A comprehensive evaluation for understanding our monitoring capability over critical regions and anthropogenic sectors will require a so-called “gap analysis” to identify an optimal configuration of observational assets targeting under-constrained regions. Additionally, as disturbances and extreme events continue to perturb the “baseline” carbon cycle, it is important to have robust plans in place to maintain continuity of key observables to improve our understanding of the baseline state, as well as to monitor the impact of gradual shifts and extreme events on the carbon cycle.

7.2. Limitations and opportunities in the spaceborne biomass program of record

Aboveground biomass maps have been produced from several past and current EO sensors, with general consensus that a combination of satellite Lidar and synthetic aperture radar (SAR) can produce the most accurate and useful maps. Lidar can accurately measure canopy height and volume without saturation under increasing carbon densities, but currently this is limited to discrete spatial samples, and limitations of conversion to biomass, and difficulty of sampling through clouds (Magruder et al., 2024). SAR data complement Lidar by penetrating through clouds and forests and provide wall-to-wall mapping and frequent observation of biomass dynamics from disturbance and recovery but with some demonstrated saturation in high biomass areas, depending on the frequency and the observational modes, and therefore require calibration for biomass estimation, often using Lidar (Dubayah et al., 2023; Xu et al., 2021). Lidar measurements from ICESat from 2003 to 2009 provided initial estimates of tree heights and above ground biomass, and were used to calibrate spaceborne SAR measurements (Saatchi et al., 2011; Baccini et al., 2012; Simard et al., 2011). GEDI's launch in 2018 provided a more reliable satellite Lidar to calibrate SAR products, reducing uncertainties in products available after ~2020 (Dubayah et al., 2022). ICESat-2 also launched in 2018, providing an expansion of observations for global satellite Lidar coverage from 2019 onwards (Neuenschwander et al., 2024). JAXA's successful 2024 launch of ALOS-4 builds on a record since 2010 of operational L-band SAR backscatter collections, and many biomass maps exist both from ALOS and current Lidar datasets.

Additional biomass estimates have also been produced through low-frequency microwave passive sensors for estimates at lower resolutions (10–40 km) (Konings et al., 2019). Passive microwave sensors like SMAP, SMOS, and AMSR-E/2 enable retrievals of vegetation optical depth (VOD), which are directly linearly related to vegetation water content. Vegetation water content can theoretically be used as a reliable proxy for vegetation carbon storage with little-to-no saturation in dense forests (Brandt et al., 2018). However, this estimation requires properly partitioning the dry biomass signal from the relative water content signal, which can require ancillary information such as leaf area index or soil moisture (Momen et al., 2017; Konings et al., 2021). Nevertheless, these VOD records extend several decades, and were recently developed into a cross-sensor combined product called VODCA extending between 1987 and 2021 (Zotta et al., 2024), and provide an additional data stream for satellite estimation that may strengthen consistency in future land flux estimates. Despite the long record of biomass and calibration efforts, estimates of biomass change from the past few decades have high uncertainties, particularly with respect to regrowth and degradation, both of which have a low signal to noise ratio for existing products.

The next few years will provide a step-change in biomass mapping capabilities. ALOS-4 will be expanded with higher temporal frequency by NASA ISRO's NISAR in 2025 (Siqueira et al., 2021) and complemented with new capabilities of P-band SAR from ESA's BIOMASS mission (Quegan et al., 2019), also in 2025. L-band and P-band SAR interferometry (InSAR) and Tomography (TomoSAR) techniques have been demonstrated to quantify biomass across all ranges from airborne systems and in synergism with Lidar data. BIOMASS offers polarimetric InSAR and TomoSAR observations to characterize forest three-dimensional structure and improve above ground biomass estimates in cloudy tropical forests (Yu and Saatchi, 2016; Ngo et al., 2022; Ramachandran et al., 2023; Quegan et al., 2019). NISAR is designed to provide biomass changes from recovering forests that constitute a significant component of land fluxes and the interannual variability of land sink (Yue et al., 2020; Xu et al., 2021). NISAR is expected to accurately map biomass up to 100 Mg/ha, and BIOMASS should be useful for higher biomass density retrievals in cloudy tropical forests, though the saturation level has not been clearly established. Integration of these SAR datasets with GEDI and ICESat-2 are expected to produce the most accurate biomass stock maps available, to date, but challenges will remain comparing these new maps to past (likely more uncertain) products for change estimation, and for longer term monitoring after these missions are completed. An important consideration is that all of these missions, except for JAXA's ALOS program, are designed for research, not operational monitoring, and thus there is no guarantee that a time series of these vital observations will be sustained past ~2030. Integration of these biomass mission datasets both with each other, through biomass harmonization (Hunka et al., 2023), with reference datasets (Duncanson et al., 2019), including NFIs and biomass cal/val sites, e.g. GEOTREES (Labrière et al., 2023), and with flux observations is crucial for reducing the large uncertainties persisting in land carbon flux estimates.

7.3. In-situ and surface atmospheric GHG program of record

In-situ airborne and surface networks offer continuous sampling of column, partial column, and near-surface GHG concentration, surface atmosphere exchange, and biomass. These data are complementary to spaceborne data in filling sampling gaps in key areas and at process relevant scales. Surface networks provide numerous additional benefits including: 1) opportunities for satellite calibration and validation, 2) training data for global data reconstructions and data assimilation, 3) informing process understanding in models, and 4) validating GHG flux inversion estimates based on spaceborne observations.

Airborne GHG profiles from research and commercial aircraft and other atmospheric vertical sampling systems are extremely valuable for independent evaluation of satellite retrievals and inversion-based flux estimates, and diagnosis of atmospheric transport model errors and biases that can lead to flux estimation bias. The NOAA Global Monitoring Laboratory (GML) monitors atmospheric profiles of GHG and related species up to 12 km altitude every 2–3 weeks using light aircraft at a dozen sites across the US, Canada, Rarotonga, Brazil, and Africa. These continuous profiles provide essential constraints on mean vertical gradient changes related to underlying surface exchange. The recent NOGAP (National Observations of Greenhouse gasses Aircraft Profiles) program samples the atmosphere in a near-continuous path around the continental U.S., addressing spatial sampling gaps and boundary constraints for high-resolution nested and regional inversions. Commercial airlines provide a powerful observational platform for obtaining free, long-term tropospheric CO_2 concentrations over a large geographical space. The JAL group began atmospheric observations in 1993 and launched the CONTRAIL Project in 2005, in order to expand their scope of observations. The CONTRAIL project makes continuous, global-scale observations of in-situ GHG concentration near major airports by regular passenger flights, consisting of five organizations: 1) National Institute for Environmental Studies, 2) Japan Meteorological Agency, 3) JAMCO Corporation, 4) JAL Foundation, and 5) Japan Airlines. Commercial aircraft being used as platforms for GHG measurements is planned by GML for the U.S. in 2025 (on Boeing 737 aircraft). AirCore flights provide an innovative atmospheric sampling system developed at GML to record GHG profiles up to the middle stratosphere that are analyzed in the lab with high precision (Karion et al., 2010). Profiles have been collected and carefully calibrated from 2012 to present day at various locations around the world (Baier et al., 2021), providing improved sampling of the troposphere relative to aircraft data.

Airborne vertical profiles also enable separation of information in boundary layer air near the surface (1000–750 hPa) from the overlying atmosphere (< 750 hPa). The ability to separate air in the lower troposphere, representing the layer of air in direct contact with the underlying surface and thus most important for process detection and attribution, from air in the upper troposphere, representing background air from more distant and potentially larger upwind spatial scales, greatly increases the sensitivity to local surface fluxes (Sarmiento and Wofsy, 1999; Gatti et al., 2021).

Ground based spectrometers record direct solar spectra in the near-infrared spectral region, offering accurate and precise column-average abundance of multiple GHG species. The Total Carbon Column Observing Network (TCCON; Wunch et al., 2011; Wunch et al., 2017) and the COllaborative Carbon Column Observing Network (COCCON; Frey et al., 2019) are global networks of Fourier transform spectrometers offering continuous sampling of GHG species throughout daylit hours with clear skies. This and other similar networks are furthermore used as transfer standards between the in- situ and space-based data to ensure that the space-based data is on the same reference scale as the in-situ data (Wunch et al., 2017; Laughner et al., 2024; Sha et al., 2024). These ground-based solar-viewing networks are useful for validating spaceborne instruments that measure reflected sunlight off the Earth's surface (e.g., OCO-2/3, GOSAT/−2, TROPOMI, CO2M, MicroCarb) because they measure a similar path through the atmosphere in a similar spectral range.

Partial column information can be retrieved from ground based spectrometers by combining total column observations from different spectral windows with assumed temporal covariance of different partial columns to perform a "secondary retrieval" that outputs partial columns consistent with the total columns observed in each of the different spectral windows, given the windows' vertical sensitivity (Saad et al., 2014; Wang et al., 2014; Parker et al., 2023; Voshtani et al., 2025). The temporal covariance assumes that partial columns near the surface vary rapidly over the course of a day due to sources and sinks, with longer temporal covariance aloft. Parker et al. (2023) demonstrated the ability to retrieve two partial columns (above and below 2 km above ground level) for both CO and CO_2 and showed high agreement with dry air mole fraction data from AirCore. As with airborne vertical profiles, partial column information from ground based spectrometers could prove to be highly valuable for increasing surface flux sensitivity and improving source/sink estimation.

On the order of 70% of FFCO2 is emitted in cities (United Nations, 2012; Gately and Hutyra, 2017). Networks of atmospheric GHG observations in urban areas have proliferated and can be leveraged for the quantification and verification of anthropogenic fluxes at local scales (Semerjian and Whetstone, 2021). These networks can also help validate or constrain vegetation models in regions with significant anthropogenic influence and fragmentation (higher temperatures, higher ambient CO_2 levels, fertilizer input). Currently, select cities are well-instrumented with ongoing and sustained GHG observations (e.g., the ICOS-Cities project, NIST Urban Testbeds, academic institution networks), with more networks proliferating globally, (e.g., Auckland, Beijing, Zhengzhou, Seoul, and more) (Semerjian and Whetstone, 2021). A prototype operational system developed in Phase I of the GHGMMIS integrates top-down and bottom-up methods into an urban-scale, operational GHG monitoring system based on flux inversions, and can be used to evaluate the capability of satellite GHG data for high-resolution emissions monitoring.

Time series of surface flux data are critical for improving estimates of CO_2 flux and above- and below-ground biomass. The eddy covariance technique has been used for decades as a direct measure of land-atmosphere CO_2 exchange on spatial scales of 1–2 km (Baldocchi, 2020). The data is globally distributed, high frequency, in many cases long term, and highly representative of climate and ecosystem space, making it an essential dataset for assessing flux dynamics at seasonal-to-decadal timescales and the roles of management and disturbance on fluxes.

7.4. Ocean program of record

The ocean plays a critical role in the global carbon cycle, absorbing approximately 30% of anthropogenic CO_2 emissions annually (Friedlingstein et al., 2026), making sustained and consistent ocean carbon observations essential for constraining global carbon budgets. While no established Program of Record exists for ocean carbon monitoring, a federation of efforts collaborates to constrain air-sea CO_2 fluxes and the ocean carbon sink. Direct measurements of surface ocean pCO_2, mostly from ships and moorings, are organized via the The Surface Ocean CO_2 Atlas (SOCAT) database (Bakker et al., 2016). As these data are very sparse (~2% coverage at monthly, 1^o x1^o), machine learning and other statistical approaches are used to develop full-coverage flux estimates. These products depend heavily on satellite-derived sea-surface temperature, salinity, and ocean-color products. Product uncertainty is largely due to significant remaining gaps in sampling at high-latitudes and in winter, as well as in seasonally ice-covered regions. Argo floats with biogeochemical sensors have the potential to contribute to ocean carbon monitoring, but concerns about systematic errors (Williams et al., 2017; Bushinsky et al., 2019) have, to date, prevented these from being integrated into the global products used in the Global Carbon Budget. Full-depth observations of carbon and other tracers (Olsen et al., 2019; Gruber et al., 2019; Müller et al., 2023) and atmospheric O_2/N_2 ratios (Keeling and Manning, 2014) provide additional constraints on the ocean sink.

NASA's PACE (Plankton, Aerosol, Cloud, and ocean Ecosystem) mission represents a significant advancement in this observational framework, providing hyperspectral ocean color measurements that enable improved retrieval of phytoplankton community composition, particulate organic carbon, and carbon export fluxes — key variables linking upper ocean biology to the biological carbon pump that plays a central role in the natural carbon cycle of the ocean. By resolving phytoplankton functional types at unprecedented spectral detail, PACE extends the ocean color record established by predecessor missions, such as MODIS and SeaWiFS, while opening new pathways for quantifying how ecosystem structure mediates ocean carbon cycling across diverse marine environments.

To improve quantification of the ocean carbon sink, sustaining and expanding both in-situ and satellite observational infrastructure requires long-term programmatic commitment to avoid data record discontinuities that would compromise trend detection and model validation. The Southern Ocean, which accounts for a disproportionately large share of ocean carbon uptake, remains particularly undersampled and represents a priority target for both autonomous platform deployment (e.g., the Southern Ocean Carbon and Climate Observations and Modeling (SOCCOM) and Constraining Ocean Carbon with Optimized Observing (COCO2) projects) and dedicated satellite mission planning. Looking forward, the integration of ocean carbon observations into operational frameworks, continuing the effort now ongoing under the auspices of the proposed World Meteorological Organization Global Greenhouse Gas Watch (WMO G3W), analogous to developments in atmospheric GHG monitoring, would strengthen the consistency and interoperability of the ocean carbon Program of Record with terrestrial and atmospheric components, ultimately supporting more accurate and policy-relevant assessments of the global carbon cycle.

7.5. Additional considerations

Three additional aspects are worth considering. First is the recognition that our current generation models need to be improved. More observations and/or measurements do not necessarily translate to improved understanding of the carbon cycle, until and unless the modeling tools at our disposal are able to 1) leverage the disparate datasets, 2) optimally use all available information, and 3) allow more robust projections of future carbon-climate feedbacks. Significant investments and development in multiple modeling frameworks are needed to keep pace with the growing Program of Record. Second, the carbon cycle operates at multiple spatial and temporal scales — from the smallest spatial scales (hundreds of meters) to scales of hundreds of kilometers. This implies that the observational coverage must span a range of spatial resolutions, which can only be reliably achieved by a tiered, diverse observing portfolio comprising ground-based, airborne, and spaceborne assets. Third, the change in atmospheric concentration resulting from surface fluxes is small. To ensure effectiveness for studies of natural fluxes, the accuracy of GHG column measurements needs to be very high, less than 0.25% (< 1 ppm) for sub-regional to regional CO_2 fluxes and less than 0.5% (< 10 ppb) for CH_4 (Miller et al., 2007; O'dell et al., 2018; Meijer et al., 2020).

8. Recommendation: hierarchical data collection to address GHG sampling gaps

The need for an integrated observing system for GHG concentration, flux, and biomass in support of operational GHG monitoring traces back to the U.S. Carbon Science Plan (USCSP; Sarmiento and Wofsy, 1999). USCSP identified several key objectives and recommended program elements to advance scientific knowledge and understanding of GHG removals and emissions at regional scale, along with application to societal needs. Several recommendations, spanning remote sensing and in situ platforms, stand out: 1) airborne vertical concentration profiles in continental regions; 2) increased continuous measurements of GHGs and associated process related tracers from towers; 3) spaceborne and surface monitoring of under-sampled regions; 4) expanded surface network of long term and experimental GHG flux measurements; 5) improved biometric inventories; and 6) new types of remote sensing for biomass.

Many of these observational recommendations have been implemented in the last 25 years, resulting in a global, multi-tiered, multi-scale, multi-agency EO Program of Record. The current GHG observing system has led to significant advances in the use of Earth System modeling for process attribution (e.g., Bloom et al., 2020; Bacour et al., 2023), and the ability to monitor global GHG emissions and removals at the scale of individual countries from space, albeit with significant uncertainties (Byrne et al., 2023). The following recommendations for a 21st century global GHG monitoring system build on early recommendations from USCSP and leverage new technologies to address many of the remaining scientific, observational, and applications gaps from space across atmospheric, flux, and biomass activities in a manner that is feasible and cost effective. Our recommendations focus on spaceborne remote sensing, but complemented by in-situ and surface based remote sensing.

We also consider ongoing and emerging measurement gaps identified more recently by the CEOS GHG Task Team, including: 1) rapid revisit and subdaily sampling, 2) polar winter and night, 3) inland and oceanic aquatic processes, and 4) sector-specific and/or localized GHG emissions in urban areas (Committee on Earth Observing Satellites (CEOS), 2024). These needs reflect collective gaps in our ability to detect and monitor emissions from abrupt events (e.g., climate extremes, disturbance, fires, permafrost explosions) spanning natural and anthropogenic sectors across populated and remote regions of the world (Fig. 2, Table 1). Likewise, the CEOS AFOLU Task Team, recognizing the wealth of planned satellite sensors covering a range of radar and Lidar altimetry data for enhanced forest monitoring over the next decade addressing longer-term biomass remote sensing needs, identified the shorter-term need for harmonized maps of space-based above-ground biomass products in support of policy relevant decisions (Committee on Earth Observing Satellites (CEOS), 2023). These needs are built into our biomass recommendations.

Our recommendations also reflect emerging carbon cycle needs as climate warming and climate extremes become more frequent and intense (Fischer et al., 2021; Seneviratne et al., 2021; Sellers et al., 2018). Climate change is giving rise to increasing frequency and magnitude of carbon sources (episodic events including fires and extreme weather, permafrost carbon emissions, microbial based methane emissions) (e.g., Miner et al., 2022; Saunois et al., 2024) and weakening carbon sinks (Sharma et al., 2023). Meeting the goals of local- to regional- scale carbon management efforts while also monitoring and preserving global carbon sinks requires multi-scale flux monitoring for losses, high-resolution biomass for live and dead carbon pools and informing heterogeneous management practices, and monitoring carbon markets. Managing carbon under changing forcing requires long-term monitoring of feedbacks under accelerating, declining, and zero emissions scenarios to detect shifts in coupled carbon-climate response from TCRE-driven to ZEC-driven (Koven et al., 2023). The timescale of the response to reduced emissions following mitigation efforts will inform understanding of the time period over which sinks respond to emissions.

8.1. Recommendations for spaceborne GHG and biomass observing system

8.1.1. GHG partial columns

Addressing intermediate scales (10–1000 km) (Fig. 1, Table 1) requires a shift in spaceborne GHG observing system design. A promising path forward is the continued development of partial column retrievals from space, leveraging ongoing work with existing ground-based and spaceborne spectrometers. Recent work leveraging a simplified Bayesian inversion shows a factor of two improvement to flux resolution and precision using partial column information in the lower troposphere (LT; $>$ 750 hPa) relative to full column data (Carroll et al., 2025b). Spaceborne mapping of GHG partial columns in at least two vertical layers, for example from the surface to 750 hPa and from the 750 hPa to the tropopause, could ultimately allow for increased sensitivity to local CO_2 enhancements, relative to regional-to-global scale CO_2 signals.

Several approaches to address spaceborne vertical GHG sampling gaps are in development and worth consideration. Multichannel systems that sample GHG wavelength bands in the NIR and thermal infrared (TIR) provide sensitivity to lower and upper portions of the atmosphere, respectively. There has been progress in extracting GHG partial columns from individual instruments, including TIR sounders (e.g., AIRS) and from NIR spectrometers (e.g., GOSAT) (Kuai et al., 2013; Kulawik et al., 2017). In principle, a harmonized approach combining different sensors to reconstruct vertical profiles with sufficient degrees of freedom (DOF) could be taken (e.g., Fu et al., 2016) but is potentially limited in its mapping capability due to the desire for coincident measurements, especially for episodic events. Single-sensor, partial-column approaches (e.g., Kuai et al., 2013; Kulawik et al., 2017), which are being used to monitor emissions from megacities (e.g., Kuze et al., 2022), will continue to improve. However, two main problems limit progress using current passive sensors: 1) existing spectrometers do not provide sufficient degrees of freedom (DOF $<$ 2) to separate information in the LT from the UT, and 2) the vertical information content of partial columns is not fully understood. Multi-spectral sounders combining radiances from TIR and NIR spectral regions show promise for obtaining multiple DOFs and multiple GHGs required for full separation of vertical information (Natraj et al., 2021; Parazoo et al., 2024). A more-exploratory approach for passive spectrometers is to retrieve from three sets of windows in the NIR with distinct vertical sensitivity, and use spatial covariance instead of temporal covariance and combining total column data retrieved in two or more spectral windows, however significant work will be needed to study the tradespace between spectral resolution and precision using passive and direct solar spectra. Likewise, a promising application of Integrated Path Differential Absorption (IPDA) Lidar based methods currently being explored using airborne campaigns is cloud slicing (Mao et al., 2023). This method involves retrieval of full columns around clouds, and partial columns to cloud tops, thus enabling the calculation of the partial column from the cloud top to ground.

8.1.2. Biomass

Lidar altimeters and SAR are naturally synergistic for mapping vegetation biomass. Based on the expected capabilities in the planned biomass Program of Record, we recommend continuity and fusion of existing and planned Lidar (GEDI, ICESat-2) and SAR (ALOS-4, NISAR, BIOMASS) records for high resolution biomass mapping (0.1–1 ha for boreal, temperate, and tropical wet and dry forests). Existing forest inventory and airborne Lidar observations provide time and space resolved biomass estimates to calibrate SAR-based mapping and monitoring of biomass globally, but require expansion to fill spatial gaps (especially in the tropics and across disturbance gradients) and repeat measurements to validate estimates of change.

For future missions, we recommend more-frequent, high-resolution sampling, to ensure long-term continuity, detection of disturbance events, and monitoring of forest conservation and restoration projects at management relevant (0.1 km) scales. We also caution against the use of very-high-resolution sensors (0.5–5 m) mapping carbon of individual trees less than 10–20 m in intact forests or for downscaling existing maps because uncertainty that is manageable at larger scales becomes problematic when disaggregated, as forest structure can be complex and overlapping, and measurements can blend signals from multiple trees, understory, and ground (i.e., lack of representativeness of forest plots for mapping individual trees) (Duncanson et al., 2025). We recommend focusing future biomass missions, and data fusion efforts, on the scale of forest plots that include many trees, to provide more meaningful maps with reduced uncertainty (Zolkos et al., 2013; Réjou-Méchain et al., 2019).

8.1.3. Frequent sampling

Existing spaceborne observing systems are generally too infrequent (1–4 samples per month) to adequately identify the timing and magnitude of rapid change, resulting from rapid (e.g., climate extremes) or abrupt (e.g., wildfires) emissions and seasonal transitions (from dry to wet in the tropics or from cold season to growing season in the Arctic) occurring over days to weeks. Mission concepts focused on frequent and continuous coverage in space and time over multiple consecutive years are needed to detect emissions and carbon cycle instabilities and provide new information relevant to improving process understanding.

For GHG, we recommend the use of imaging spectrometers to conduct sit-and-stare sampling from geostationary or highly-elliptical orbit (Nassar et al., 2019; Natraj et al., 2021; Parazoo et al., 2024) for more frequent (sub-daily) spatial mapping of regions. High spatial resolution ($<$ 1 km) and measurement precision ($\sim$ 0.25% for CO_2 and CH_4) will facilitate localization and sensitivity to weaker point-source and diffuse GHG emissions to improve the effective (cloud free) sampling rate. The CO2M mission, comprising a constellation of three satellites, will dramatically increase the temporal sampling frequency of CO_2 and NO_2 compared to single-satellite approaches, enabling more frequent revisits over emission hotspots and improving the ability to disentangle natural from anthropogenic greenhouse gas fluxes.

For more frequent global sampling, we also recommend combining global low earth orbit flux mappers with continuous, spatially distributed upward looking ground-based spectrometers (Wunch et al., 2017) to provide more comprehensive constraints on time-mean flux and its temporal variability, as well as the timing of episodic events (e.g., Voshtani et al., 2025). Critically, these ground-based spatially distributed upward looking networks must collect continuous data throughout all satellite mission lifetimes to provide validation for each individual satellite mission and provide a consistent and accurate link between satellite missions.

Planned biomass missions are expected to provide sufficient cloud free sampling frequency. NISAR is designed to provide cloud-free imagery on approximately weekly time intervals to capture vegetation biomass dynamics from various natural disturbances such wildfire, storms, and human-induced land use activities. Sentinel-1 A,B, and C series from ESA have been designed to also provide weekly cloud-free imagery to allow for frequent sampling of global vegetation and to compensate for the lack of optical imagery due to clouds.

8.1.4. Critical regions

Tropical and Arctic land regions, and most of the global ocean, remain poorly observed for much of the year due to clouds, aerosols, darkness, and poor signal strength (e.g., slow, diffusive flux from permafrost and oceans). As a result, partitioning of the global carbon sink between land and ocean, and between northern and tropical regions, remains a challenge (Kondo et al., 2020; Chatterjee et al., 2017). Wide swath area mapping from shortwave passive systems can improve sampling, but will continue to be challenged by atmospheric scattering, retrieval biases under smoky and dusty conditions, and sampling gaps from clouds and darkness. This persistent, regionally-specific lack of data coverage at global scale hinders full closure of the global carbon budget (Friedlingstein et al., 2024). We recommend the use of active and shortwave passive systems to achieve improved coverage between clouds and during night, and improved signal over oceans. For passive spectroscopy, fine spatial resolutions (< 60 m) offered by point-source imaging spectrometers can improve sampling of CH_4 and CO_2 plumes in cloudy land areas without the need for high spectral resolution (Cusworth et al., 2019; Galli et al., 2012; Jongaramrungruang et al., 2021; Wilzewski et al., 2020; Thorpe et al., 2023), though work is needed to study tradeoffs between spectral resolution and GHG precision/accuracy.

To improve sampling of ocean regions, passive systems such as OCO-2/3 and GOSAT point the instrument's aperture near the “glint spot” where sunlight is specularly reflected by the surface. These measurements are precise but are also subject to systematic errors, which are poorly characterized. Dedicated efforts are needed to identify and remove systematic errors in ocean glint column retrievals and atmospheric assimilations will thus be crucial for maximizing the usefulness of passive sensors. Spatially- and temporally-resolved bias corrections are likely to pay large dividends in our understanding of land-ocean partitioning and ability to reconcile bottom-up estimates. Active systems (e.g., IPDA Lidar) offer improved sampling year round including polar darkness and in cloudy regions, as has been demonstrated from airborne Lidar (Mao et al., 2023). Airborne GHG Lidar has been demonstrated to work well when measuring atmospheric CO_2 over oceans, inland water, and transitions from oceans to land near coastal cities (Mao et al., 2023).

Observations of critical land regions such as boreal and tropical ecosystems have become available using active microwave sensors to detect the freeze-thaw cycles and permafrost monitoring, and loss of carbon from wildfire and drought-induced tree mortality (Tao et al., 2022; Saatchi et al., 2011; Mavrovic et al. 2023).

8.2. *Recommendations for in-situ GHG and biomass observing system*

8.2.1. *Atmospheric GHG*

Our broad recommendations for the in-situ GHG network are 1) expansion of coverage and frequency of column, profile, and near-surface GHG sampling by upward looking spectrometers, and airborne and tower GHG in-situ sampling platforms including research and commercial aircraft, AirCore, and surface towers for ongoing spaceborne flux and retrieval cal/val, 2) coordination of upward-looking spectrometers with in-situ vertical sampling efforts for more robust and targeted testing and development of partial column retrieval algorithms for spaceborne applications, and 3) dedicated urban GHG testbeds in representative regions and biomes to support spaceborne flux and retrieval cal/val in urban environments.

8.2.1.1. Airborne and surface. Measurements of GHG concentration from upward looking spectrometers and in-situ vertical profiles provide critical cal/val data for spaceborne column GHG retrievals but are not currently well suited for characterizing spaceborne partial columns. Spectra from the TCCON and COCCON networks are being used to test updates to the spectroscopy used for retrieval of column CO_2 and CH_4 from OCO-2/3 (Thompson et al., 2012; Oyafuso et al., 2017; Payne et al., 2020) and TROPOMI (Galli et al., 2012). Likewise, in-situ profiles from aircraft and AirCore platforms are used to validate posterior flux estimates from spaceborne GHG inversion systems but are not widely used to directly test spectroscopy or validate retrievals. To build on these efforts, we recommend coincident observations of ground-based spectrometers with in-situ vertical profiles to greatly increase the confidence of the transfer standard for spaceborne vertical profile data. In-situ profiles over ground-based spectrometer networks that cover a range of atmospheric states (e.g., low vs. high air mass, humid vs. dry) would provide a broader set of observations for which the true atmospheric state is known to test spectroscopic improvements. For these, a combination of AirCore and more frequent near-surface profiles is likely ideal, as frequent near-surface profiles will help validate the rapid variation of gas concentrations in the boundary layer, while the more comprehensive AirCore profiles would allow validation of troposphere-stratosphere separation for methodologies, such as Saad et al. (2016). Though more challenging, expansion of coverage and observation frequency of vertical profiles by airplane would offer several additional benefits not possible from the AirCore platform, including 1) frequent and sustained profiles in urban environments needed to monitor emissions change, 2) sampling at cruise altitude in the stratosphere needed to monitor GHG exchange between the stratosphere and troposphere, and 3) sampling over ocean basins to validate and inform air-sea exchange.

8.2.1.2. Towers. Likewise, long-term ground-based GHG measurements from globally-coordinated networks can help constrain overall fluxes globally, regionally, and locally to evaluate flux estimates from top-down and bottom-up models. Long-running background sites and tall tower networks are critical for monitoring and constraining global and regional trends, respectively, in CO_2 and CH_4 budgets (Peters et al., 2007; Bruhwiler et al., 2014; Byrne et al., 2023). Continuation and expansion of these networks from northern mid-latitude countries into the Arctic and tropics will be critical for monitoring abrupt and long-term change in managed and climate sensitive regions (Sweeney et al., 2016; Parazoo et al., 2016; Commane et al., 2017; Botía et al., 2022). The high cost of existing measurement techniques, including air sample analysis (flask-based) and commercial GHG analyzers (continuous), has limited expansion of existing networks. Future research and development in the area of lower-cost sensors with sufficient accuracy can alleviate the cost burden of a more spatially- and temporally-dense in-situ network, similar to that which is currently available for meteorological parameters used in NWP (e.g., H. Bauer, et al., 2015). We reiterate previous recommendations to combine remote sensing and in-situ data as the best strategy for estimating global and regional greenhouse fluxes in the long term (e.g., Crisp et al., 2018; Byrne et al., 2023).

8.2.1.3. Urban. For urban regions, we recommend selecting highly-instrumented cities spanning the biomes with sustained long-term observations networks, to serve as validation points for spaceborne retrievals and emissions estimates based on other methods that are more scalable (e.g., using fluxes derived from a dense tower network to validate fluxes derived using OCO-3 and CO2M). Representative cities will be key given cost and logistical considerations of deploying and maintaining high-accuracy GHG urban networks. Targeted calibration of spaceborne column and partial column data in urban environments will be critical due to retrieval challenges such as surface albedo contrasts (e.g., paved surface; proximity of most cities to coasts and water bodies) and environmental conditions (e.g., increased aerosol loading). For the same reason, select cities will serve to develop robust scaling capabilities. Additional research and modeling advances can reveal more efficient ways to assess emissions for cities, such as: 1) deploying lower-cost in-situ sensor networks for monitoring both GHGs and air quality species (e.g., BEACO2N) for better source attribution and coupling with air quality satellites such as TEMPO; 2) conducting periodic flight campaigns for snapshot estimates to confirm inventories; 3) using vertical profile measurements from commercial aircraft near cities (e.g., IAGOS, CONTRAIL, and the nascent NOAA / GML commercial airline project); 4) deploying solar-viewing remote sensing spectrometers (e.g., Dietrich et al., 2021), and 5) using only one or two stations in a city (Sargent et al., 2018), while assessing the impact on uncertainties relative to estimates using a denser, more complete network.

8.2.2. GHG flux and inventories

Our broad recommendations for the GHG flux and inventories are 1) expanded flux tower network in critical regions and integration with remote sensing data through data fusion techniques, and 2) expanded wetland and ocean observing systems to better constrain aquatic environments and their space-time variability.

8.2.2.1. Land. We recommend the combined use of flux tower data with remote sensing constraints via ML and data reconstructions for global, contiguous, gap-free constraints of global carbon cycling following techniques developed over the last decade (e.g., Jung et al., 2020). It is critical that FLUXNET communities continue to collect flux measurements to complement and in support of spaceborne biomass systems, expand into poorly-represented tropical regions and along major gradients of climate and undisturbed, managed, and disturbed land, and make data openly available to the scientific community to support studies to reduce bias and improve data quality to ensure ongoing assessment of climate anomalies and long-term change under current and future forcing. Free Air CO_2 Experiments (FACE), which continue to improve our understanding of the sensitivity of vegetation to carbon and climate (Ainsworth and Long, 2005), will also be critical. Decoupling of CO_2 and climate forcing under declining emissions will likely require reverse FACE experiments to track changing sensitivities in support of dynamic model calibration and benchmarking. Expansion of Biomass Reference Measurement networks such as GEOTREES (https://geo-trees.org), which estimate above-ground biomass from forest plot inventories of tree height, diameter, and growth, along with airborne and terrestrial Lidar scans, and are needed for ongoing monitoring and validation of spaceborne biomass. Below-ground biomass and soil carbon processes are extremely challenging to monitor from space, therefore in-situ measurements of changes across terrestrial ecosystems are critical.

Table 3

Summary of GHG and biomass observing system recommendations. These GHG community driven recommendations address sampling and science gaps and carbon management needs across atmosphere, land, ocean, and wetland areas. The observing system prioritizes spaceborne monitoring for the 2028 Decadal Survey but acknowledges the need for in-situ (airborne and towers) and surface (upward looking spectrometers) networks to fill sampling gaps and calibrate and validate satellite retrievals.

Carbon Management Need			Science Gap	Sampling Gap	Proposed Satellite Observing System	Proposed Surface and Airborne Observing System	Description	TRL Development Opportunities	Cal / Val Opportunities
1	2	3							
X	X		Natural and fossil flux in small regions (10–100 km).	Vertical GHG	Multichannel GHG area mappers in LEO, targeting NIR and TIR bands with combined sensitivities in LT and UT. A single, multichannel sensor is desired for multi-species sampling.	Expanded, representative urban testbeds focused on tower, airborne, and surface spectrometers to fill gaps and validate satellites.	Partial columns (LT + UT) to improve sensitivity to underlying surface flux, and reduce background influence.	Trade studies to optimize multi-band NIR and TIR partial column retrievals.	**Spaceborne GHG**: Expansion of airborne profile (Research, Commercial, AirCore) and upward looking FTIR (TCCON, COCCON) networks over land and ocean. **Land / Aquatic flux**: Expansion of concentration and flux towers into tropical and arctic regions and over wetlands **Ocean flux**: Network that augments existing ship-based approaches with greater coverage in coastal and poorly-sampled regions, eddy covariance, Saildrones and autonomous vehicles, and expanded coverage of ARGO / BGC-Argo profiling floats.
	X	X	Abrupt and slow carbon climate feedbacks in key regions (e.g., Arctic and tropics).	Tropical and Arctic GHG	Similar observing system as above, targeting sub-daily partial columns in Tropical and Arctic regions from GEO and HEO, respectively	Continuous sampling from in situ profiles from airborne and tower networks to fill gaps and validate satellites.	Combined vertical sampling with sustained, rapid revisits in targeted regions to monitor feedbacks	Trade studies to optimize sampling strategy (spatial, temporal, spectral, geographic extent)	
	X	X	Spatially explicit mapping of air-sea gas exchange.	Ocean GHG	GHG area mappers in LEO consisting of (1) Glint viewing spectrometer, and (2) Nadir viewing Lidar. Cal/Val against expanded commercial-based ocean airborne sampling.	Regular sampling from commercial and research aircraft.	Lidar to observe over any surface, enabling continuous sampling over land and ocean. Glint viewing spectrometers offer increased precision.	Trade studies to optimize Lidar retrieval, characterize ocean bias via ground validation.	
X	X	X	Arctic permafrost emissions in winter; Respiration and fossil emissions at night and in winter.	Night and Winter GHG	Combined multi-scale GHG point source and area mappers in LEO, anchored by Lidar for high spatial resolution, and multichannel spectrometers for area mapping.	Continuous sampling from in situ profiles from airborne and tower networks to fill gaps and validate satellites.	Leverage cross sensor strengths using coincident observations from multiple sensors on the same platform.	Trade studies to optimize multi-instrument retrieval.	
	X	X	Monitoring of ecosystem regrowth and degradation at ~1 ha over multiple decades.	Biomass Change	Fusion of spaceborne Lidar and SAR in LEO, leveraging Lidar as training data for SAR-based mapping	Above ground biomass from forest plot inventories. Continuation of existing sites, and expansion to new regions and ecosystems.	Lidar and SAR are synergistic, and their fusion could enable high resolution biomass maps, and accurate monitoring of present data and future vegetation carbon dynamics.	Trade studies leveraging existing and planned Lidar (GEDI, ICESat-2) and SAR (ALOS-4, NISAR, BIOMASS) for data fusion model development.	Expansion of GEOTREES.

8.2.2.2. Oceans. Expanded ocean observing systems of both surface-ocean and water-column properties are needed to better constrain the space-time variability of the ocean carbon sink, and for full attribution of drivers of sources and sinks due to air-sea CO_2 flux, ocean circulation and mixing, biological productivity, and lateral fluxes. A network that augments existing ship-based approaches with greater coverage in coastal and poorly-sampled regions (especially during winter months), eddy covariance measurements made at sea (Dong et al., 2024), Saildrones (Sutton et al., 2021) and autonomous vehicles (such as AUVs and gliders), and the expanded coverage of ARGO/BGC-Argo profiling floats (Claustre et al., 2020). We also recommend a focus on development of new autonomous technology for measuring additional carbonate chemistry variables, such as Dissolved Inorganic Carbon (DIC) or Alkalinity, which can be deployed on moorings and drifters to capture the long-term evolution of the full seawater carbonate system. Additionally, datasets should focus on synthesizing observations from aircraft, ships, and shore-based stations. Improved methodology is also needed to better constrain and separate anthropogenic carbon from variability in the natural carbon field. Decadal estimates of whole-ocean anthropogenic carbon storage depend on the continuation of repeat hydrographic observations through programs such as GO-SHIP.

8.2.2.3. Wetlands. The community recommends expansion and investment of existing wetland monitoring networks (e.g., the National Estuarine Research Reserves (NERR), Buskey et al., 2015), increasing focus on human impacts related to restoration (Couvillion et al., 2013) and intervention (O'Connor et al., 2020), new ground measurements including eddy covariance towers for wetlands (McNicol et al., 2023), studies of carbon permanence including synthesis of near-term surface elevation monitoring (Cahoon, 2024) and high-resolution drone surveys (Ganju et al., 2024), and lateral flux from lakes and rivers to oceans, including improved intermediate salinity zone and inundation class mapping (Holmquist et al., 2018; Arias-Ortiz et al., 2024). For long-term carbon fluxes, we recommend: 1) expanded datasets of radioisotopically dated soil cores with precise elevation to calibrate process models (Holmquist et al., 2024); 2) new studies on temperature and soil structure effects on decomposition (Spivak et al., 2019); and 3) a substantial investment in understanding the effects of global change factors and rapid evolution on below-ground plant traits (Vahsen et al., 2023).

8.3. Complementary data

Independent datasets, beyond the primary GHG concentration, biomass, and surface flux time series, are needed to constrain the locations and processes responsible for the carbon sources and sinks, and better characterize their variability at multiple spatial and temporal scales. In addition to primary GHG data (CO_2, CH_4, CO), global spaceborne, airborne, and surface sites should include complementary data such as SIF, OCS, O_2, and carbon and oxygen isotopes (^{13}C, O_2) to simultaneously constrain larger gross uptake fluxes of CO_2 and CH_4, and partitioning between biogenic and fossil processes, in the land, ocean, and aquatic systems. Measurements of carbon CO, radon (SF6), nitrous oxide (N_2O), nitrogen dioxide (NO_2), ethane, hydrogen cyanide (HCN), formaldehyde (H_2CO), and CH_4 isotopes ($^{13}CH_4$) will be necessary to constrain emissions from wildfires, permafrost, agriculture, and point sources. Spaceborne estimates of fire extent, fire radiative power, and above-ground biomass can be combined with CO to more accurately quantify fire carbon emissions with varying assumptions about emission factors, dry matter mass, and fire weather transport. Activity data, such imaging or reporting of activity associated with anthropogenic emissions related to construction of energy generation units (EGUs), oil and gas facilities, and development in urban areas will provide essential bottom-up constraints.

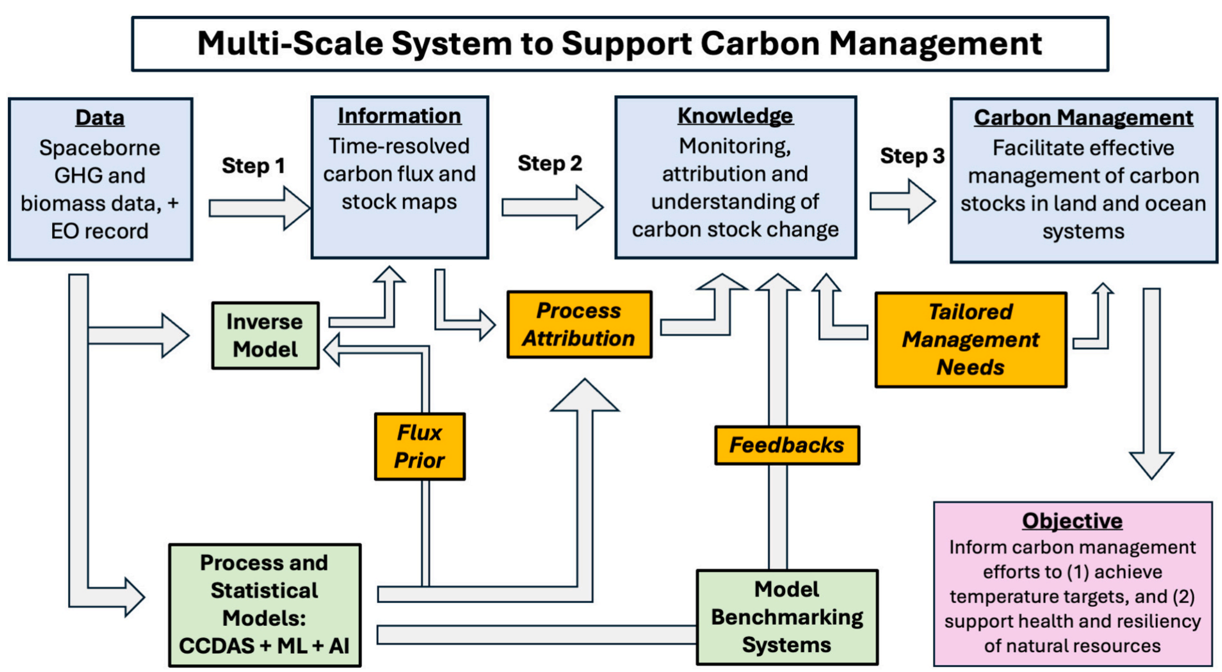

Fig. 3. Hierarchy of a multi-scale greenhouse gas observing system implementation plan. The effective use of GHG observations to address carbon management needs in support of GHG mitigation requires generation of information and knowledge from satellite, airborne, and surface data. Key gaps preventing flow of information from data to carbon management includes prior knowledge and attribution of carbon fluxes, carbon cycle feedbacks, and tailored management needs (orange boxes). We propose integration of observing system data with information technology (green boxes) from Earth System Models, carbon cycle data assimilation systems (CCDAS), machine learning (ML), and artificial intelligence (AI) to generate information about flux and biomass change, and knowledge of mechanistic drivers. From this knowledge, we can better facilitate effective carbon management of carbon stocks and inform efforts to stabilize climate and support natural and managed resources. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 4
Wisdom traceability matrix for global GHG mitigation needs. This provides a mapping from data to actionable information of value to stakeholders to meet carbon management needs. The ability of GHG observing systems to inform carbon management is limited by remaining sampling gaps in the Program of Record, summarized on the right.

Wisdom Traceability Matrix: Global Greenhouse Gas Mitigation Needs					
Wisdom	Knowledge	Information	Data	Missions	Gaps
Manage nationally determined contributions (every 5 years)	**Carbon Stock Change**	**Anthropogenic + Natural Net Carbon Flux at National Scale** (100–1000 km)	**Carbon Flux Maps**	**Carbon Flux Mappers**	**Remote Sensing Needs:** •GHG Partial columns (multichannel spectrometers; combined spectrometers and LiDAR) •Under-sampled regions (non-forest lands, rivers, wetlands, coastal zones, Southern and Arctic Oceans, tropics, Arctic) •Cloudy regions (small footprints) •Winter and nighttime data (LiDAR; thermal sounders and/or spectrometers) •Better characterized ocean bias (via ground validation, TCCON, COCCON) •Long term monitoring (10+ years) •Complementary data (NO_2 for urban attribution) **Airborne Needs:** •Vertical profiles (AirCore, commercial and research aircraft) •Expanded coverage over ocean basins •Frequent, long term sampling **In Situ Needs:** •Ongoing growth of surface data network (flux towers, ships, saildrones, autonomous vehicles, atmospheric co2 and surface ocean fco2 network) over terrestrial, oceanic, and aquatic surfaces
Near Term GHG Mitigation (5–20 years)	**Carbon Stock Change and Process Attribution**	**Net and Component Carbon Flux and Stock at Intermediate Scale** (10–500 km)	**Harmonized Carbon Flux and Stock Maps**	**Carbon Flux + Stock Mappers**	**Remote Sensing Needs:** •Harmonized biomass, extended over multiple, consecutive years •Continuity of red SIF over ocean •Information on irrigation and disturbance •Complementary data (e.g., CO, N2O, Isotopes, SIF, and OCS) **In Situ Needs:** •Expanded surface data network •Land: Regular biomass data collection (e.g., GeoTrees), Rsoil chambers •Wetlands / Coastal Zones: river gauges, biogeochemistry
Long Term GHG Mitigation Strategy (10–50 years)	**Carbon Cycle Feedbacks**	**GHG Flux Prediction at Intermediate Scale** (10–500 km)	**Integration of Carbon Flux and Stock Maps with Models**	**Carbon Flux + Stock Mappers**	**Remote Sensing Needs** •Tipping point region focus (via GEO and HEO sampling) **In Situ Needs:** •FACE and Reverse FACE experiments

8.4. Summary of observing system recommendations

We recommend a globally-unified GHG observing system focused on sub-seasonal-to-decadal monitoring of carbon fluxes and stocks at intermediate spatial scales. The observing system should focus on frequent, sub-daily GHG vertical profiles for carbon emissions and removals, continuous time series and data fusion of biomass from Lidar and SAR for carbon stocks, and expanded coverage of tropical, high latitude, and oceanic regions to monitor carbon cycle tipping points and feedbacks (Tables 3, Figs. 1–2). Long-term spaceborne vertical profiles of CO_2 and CH_4 will serve as the foundation of the observing system, enabling sustained monitoring of slowly (decadal) and rapidly varying (days to weeks) diffuse fluxes from natural and anthropogenic sources at unprecedented spatial scales (5–100 km) under present and future climate. Frequent sampling (sub-daily) and small satellite footprints ($<$ 1 km) will ensure that abrupt emissions, including sudden losses of carbon in tropical and Arctic regions typically hidden from satellites by clouds, do not go undetected. Harmonized biomass data will augment our ability to monitor the accumulation and loss of carbon due to management practices, natural or anthropogenic disturbance, and recovery. The observing system should combine global coverage for regional and national carbon closure, and targeted monitoring of key regions to monitor tipping points. Spaceborne active and passive GHG remote sensing tools will be needed to address multiple global observing challenges in key regions related to cloud cover (tropics), polar night (high latitudes), and dark surfaces (ocean). A constellation of polar orbiting and geosynchronous orbits will be necessary to achieve global coverage and targeted monitoring of key regions. This system should be complemented by expanded surface and airborne networks for oceanic and terrestrial/aquatic ecosystems for calibration, ground truthing, and study of under-sampled regions, such as non-forest lands, rivers, wetlands, coastal zones, the Southern and Arctic Oceans, tropics, and permafrost regions. The observing system should also be augmented by complementary constraints of GHG emission and removal processes (photosynthesis, wildfires, facility scale oil and gas emissions) from GHG tracer and activity data, which are essential for process attribution and informed decision support.

This unified, operational system for GHG monitoring will be essential to inform policy making, urban planning, regulation compliance, disaster and disturbance response, sub-seasonal to seasonal forecasting, climate projection, and other carbon management needs requires a unified observing system capable of hindcasting changes in GHG removals and emissions in the past (previous 5–20 years), monitoring sudden changes happening at present, and forecasting changes in the near-term (monthly, seasonal, annual) and distant future (5–20 years).

9. Decision support framework linking actionable knowledge to observing systems

9.1. Overview

In the previous sections, we summarized the collection of scientific knowledge, informational tools, and observations that have revolutionized modern GHG science. We have also identified critical opportunities to build on these tools with advances in ML, data assimilation, inverse modeling, and next-generation observing systems. Here, we provide an overview of our community vision to synthesize observation and modeling tools into more accurate, effective, and timely information for decision support. We propose a two-way flow between data and actionable information, to meet the evolving needs of carbon management, while leveraging the growing ability to observe and interpret scientific phenomena at policy-relevant scales.

9.2. Wisdom traceability

Data from satellite, airborne, and field observing systems is essential for identifying and characterizing scientific phenomena arising from natural and anthropogenic processes. These data provide the foundation for carbon management. The deployment of advanced information technology (inversions, process and statistical models, and benchmarking systems) to address key information gaps (flux priors, process attribution, sign and magnitude of natural feedbacks, and mitigation progress and opportunities) enables a more seamless transformation of data to increasingly informative, actionable information (Fig. 3 and Table 4). We recommend three main steps:

Step 1: Information from data-constrained models helps to interpret and communicate scientific data in a meaningful way. This step involves use of radiance and geophysical quantities from multi-tiered GHG and biomass observing systems as constraints in bottom-up land and ocean models and top-down inverse models, and development of multi-scale maps of biomass and GHG flux. Continuous, low-latency, evidence-based, data-constrained information is critical for verifying GHG mitigation strategies.

Step 2: Knowledge includes scientific research and attribution studies that help to identify the underlying causes and drivers of phenomena. Knowledge is essential for tracking and understanding changes in GHG emissions and removals, assessing progress in emissions reductions, and developing effective strategies and policies to mitigate emissions and manage removals.

Step 3: The collection of actionable knowledge is needed to track NDC progress and carry out near- and long-term GHG mitigation efforts.

Section 8 summarized GHG and biomass observing systems essential to Step 1. Below, we provide additional details and recommendations for Steps 1–3.

9.2.1. Data to information (Step 1)

The ability to transform GHG observations, describing the wind- and flux-driven atmospheric GHG state, into information that describes the distribution of GHG emissions and removals over time requires integration of GHG concentration and biomass data within land and ocean models and atmospheric inverse models.

Flux inversion methods, discussed in Section 6.1, are the primary tool to infer land and ocean net carbon exchange from GHG concentrations. Our recommended observing system could, in principle, provide sampling of the horizontal, vertical, and temporal structure of GHG gradients across global land and ocean regions sufficient to meet GHG tracking and reporting needs at ecosystem-to-country scale. However, due to logistical (cost, downlink capacity) and physical (clouds, darkness) challenges of sampling continuously in space-time at high precision, inverse systems typically require assumptions about prior land and ocean carbon fluxes, along with their uncertainties, to effectively set-up the optimization process. However, it is clear from the discussion in Section 4 that both land and ocean models have significant mean state errors, likely related to their underlying physical states and model assumptions. Consequently, enhancing the accuracy of prior flux magnitudes and spatial partitioning across land and ocean, and their associated uncertainties, is essential for improving top-down flux inversions in support of information and knowledge needs. Assimilation of physical and biogeochemical properties into a CCDAS is a promising path for reducing, but not fully solving, mean state biases in land and ocean models. We therefore recommend a three-stage model-data integration framework: 1) use of a CCDAS to incorporate field and remotely-sensed carbon flux and biomass data into land and ocean biogeochemistry models to correct and improve flux priors; 2) incorporation of improved data-constrained flux priors and remotely sensed and in-situ atmospheric GHG concentration data within regional and global inversion systems to address remaining spatial or temporal uncertainties in spatial and temporal patterns of net carbon flux; and 3) validation of constrained fluxes against flux tower observations and surface and airborne GHG observations.

9.2.2. Information to knowledge (Step 2)

The ability to gain knowledge from time-resolved flux information comes from scientific research and process attribution studies. Process attribution includes 1) separation of net fluxes into process components and 2) disaggregation of net and gross fluxes into finer temporal and spatial scales.

9.2.3. Component fluxes and pools

The net exchange of carbon between land and the atmosphere is a small residual of two large vertical flux components: 1) carbon uptake through gross primary production (GPP) and 2) carbon release through ecosystem respiration, fossil fuel emissions, and fires. To provide process attribution and improve near- and long-term prediction, it is essential to understand how these component fluxes contribute to changes of net carbon exchanges from daily-to-decadal time scales and from the tropics to high latitudes. GPP, fossil fuel, and fire emissions can be estimated using multi-species information (e.g., SIF, OCS, CO), as described in Section 8.3.

Unlike GPP and fire-related carbon emissions, direct observations or proxies for ecosystem respiration are limited, with only sparse in-situ measurements available for soil respiration, a key component of ecosystem respiration. Consequently, ecosystem respiration carries the highest uncertainty among these carbon flux components. Leveraging an expanded network of in-situ soil and plant respiration measurements, particularly across tropical and high-latitude regions, with emerging ML techniques to estimate soil respiration, could be crucial steps towards reducing respiration uncertainties.

Finally, the net exchange of carbon inferred from atmospheric CO_2 and CH_4 observations reflects the vertical exchange of carbon between land or ocean reservoirs and the atmosphere. However, a portion of the carbon accumulated on land is redistributed laterally — either transported to other regions through trade or exported to rivers and oceans by runoff. Consequently, the actual change in carbon stocks, which is the target metric for the GST, is determined by the balance between net carbon accumulation and these lateral transfers via runoff and exports. Accurately measuring lateral carbon flows remains challenging due to high spatial variability and the difficulty of quantifying carbon within subsurface and water pathways. Previous studies have applied heat constraints to estimate hemispheric riverine carbon fluxes (Resplandy et al., 2018). Nonetheless, improved quantification of lateral transport with finer spatiotemporal resolution and higher accuracy is urgently needed to better resolve carbon budgets across reservoirs and to create datasets that inform policy.

9.2.4. Gap filling and downscaling fluxes and pools

Information on the component flux processes and carbon pools driving net removal and emission of GHGs, such as GPP, respiration, and

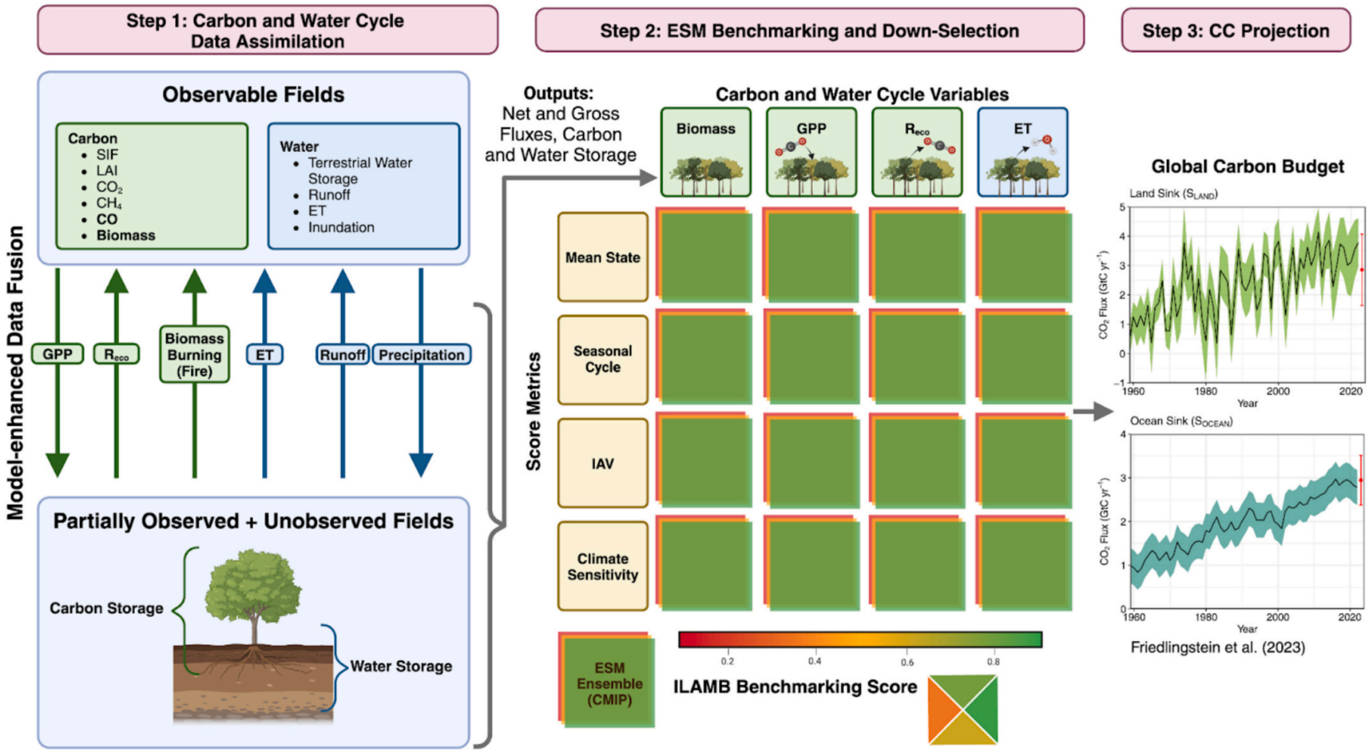

Fig. 4. Model benchmarking framework for carbon-climate feedback projections. Reductions in atmospheric CO_2 growth resulting from successful national and international GHG mitigation programs will alter CO_2 fertilization effects and potentially reverse land and ocean carbon sinks. The ability of Earth System Models (ESMs) to accurately predict ecosystem responses to changes in forcing will require improved benchmarking systems for constraining ecosystem sensitivities to past, present, and future climate. We propose the use of carbon and water cycle data assimilation systems (Step 1) to generate observation constrained fields for more complete benchmarking of ESMs (Step 2) and carbon cycle projections (Step 3).

fires, are powerful and essential for attribution and interpretation of net emissions and removals. However, in many cases the methods used to develop component flux products are done independently and not fully consistent, which can create imbalances in magnitude and uncertainty between net and component fluxes. Data fusion tools are needed to fill gaps and exploit strengths across like datasets (e.g., SAR, Lidar) and related properties (e.g., vegetation structure and function, related but opposing carbon fluxes), for upscaling of spatially-sparse surface data, for downscaling of spatially-coarse remote sensing information, and for contiguous mapping across scales. Likewise, integration of diverse carbon flux component (GPP, fire) and pool (biomass) constraints from ground and spaceborne observations vis-a-vis CCDAS will be needed to account for uncertainty in observational inputs, process representation, and functional relationships, and provide consistency of carbon fluxes and pools across spatial and temporal scales. The system should be flexible in its ability to incorporate new observational constraints and process understanding and constrain fully coupled carbon-water-energy cycles for additional process attribution.

9.3. Knowledge to action (Step 3)

The objective of a global GHG observing system is to provide information and knowledge in support of actions required to achieve national emissions goals. The primary action to achieve and maintain emissions goals are emissions reductions and management of near- (5–20 years) and long-term (10–50 years) natural feedbacks (e.g., Schimel and Carroll, 2024). The final step in providing actionable climate information is making more effective and operational use of knowledge of carbon flux change and underlying drivers and feedbacks to track NDCs and carbon markets and inform near- and long-term GHG mitigation opportunities.

Long-term (multi-decadal), low-latency (6–12 months) tracking of net and gross carbon fluxes and stocks enabled by multi-tiered GHG observations and hierarchical inverse modeling, data assimilation, and ML tools will be needed to consistently and reliably track changes in country level GHG budgets every 5 years, evaluate country-level progress towards achieving NDCs in support of the GST, and update NDCs accordingly. We recommend this system also be used to determine historical change in GHG source and sink processes and inform mitigation of sources and management of sinks across energy, industry, and AFOLU sectors.

Building the capacity to link EO data to ecosystem, carbon cycle, and climate models is key to understanding and predicting changes in future fluxes as a function of land use and climate change, with both the magnitude and direction of fluxes unclear due to complex feedbacks (e.g., drought and fire) that may slow carbon sinks, or CO_2 fertilization and warming which enhance sinks. We therefore also recommend the use of model-data integration systems, such as a CCDAS, to quantify and constrain uncertainty in predictive models, providing weighted uncertainty estimates based on model performance across a range of carbon variables and score metrics (Fig. 4). Prototypes of a CCDAS for projections have been developed in the context of emergent constraints (Wenzel et al., 2014; Hall et al., 2019; Winkler et al., 2019; Barkhordarian et al., 2021; Liu et al., 2024; Cox et al., 2024), which exploit correlations between present-day variability and long-term response in carbon-climate model ensembles in conjunction with observations to constrain future projections. These approaches can be reframed into a data assimilation context, such as hierarchical emergent constraints (Bowman et al., 2018; Williamson and Sansom, 2019). An important aspect of these approaches is the selection of relevant observations. Benchmarking systems, such as the International Land Model Benchmarking (ILAMB) tool, which rely on diverse carbon and water observations, are essential for assessing model performance in historical and projected carbon cycle change. Benchmarking systems currently rely on diverse and inconsistent datasets, and could benefit greatly from self consistent, wall-to-wall constraints offered by carbon cycle data assimilation (Schimel and Carroll, 2024). Carbon management policy opportunities that could be informed by benchmarked ESM predictions include: 1) adjusting carbon neutrality targets according to increasingly positive or negative feedbacks; 2) augmenting the GHG observing system to target and track regional feedbacks; 3) increasing investment in negative emissions technologies; and 4) accelerating development of forestry and agricultural management strategies.

9.4. Interagency collaboration

For the operational system to be successful, we stress the need to develop and leverage partnerships to share resources and capabilities. National space agencies provide trusted and reliable global data, targeting Earth System processes of broad interest to society, but often at low latency and lacking direct and immediate value to stakeholders. Other national agencies provide trusted and reliable data in an operational capacity (e.g., weather observations, in-situ observations, activity and economic data) and develop measurement standards and guidelines to ensure the quality and inter-operability of data collected across providers. The commercial sector can quickly deploy constellations of satellites in an operational manner, providing high-resolution maps of the land surface and GHG concentrations at low latency, but often with higher cost to users and lack of transparency. The commercial and private sector can offer computational and personnel resources needed for efficient data processing, but lack scientific expertise. International, interagency collaboration is needed to maximize overlapping strengths and reduce gaps in technology and expertise.

10. Opportunities for earth science to action coordination

10.1. Best practices for engagement and coordination

Bridging scientific research with stakeholder engagement and policy making is critical, along with integrating robust data integration frameworks while engaging users with analysis-ready product delivery; thus, these roles can be fulfilled and extend beyond establishing new observing systems. As we continue to learn more about ecosystems and the Earth System from these new observing systems, more tailored recommendations to unify the intersection of science, technology, and societal value are necessary. These recommendations include: 1) the delivery of products to end-users, 2) leveraging collaborative opportunities and partnerships, 3) generating novel architectures while creating new services, 4) interweaving societal value into science communication, and 5) forging a transparent, actionable pathway that effectively translates data cohesively for a diverse and extensive array of user groups.

Principally, the delivery of a universal user-enabled data discovery and Application Programming Interface (API) platform must be tailored and prioritized with data literacy and accessibility at the forefront, along with distribution to all end-users globally, ensuring capacity-building through effective data leveraging and syntheses. This wide net of accessibility not only nurtures a robust community and assures scientific merit is retained, but stimulates the future evolution of instrument design, data synthesis, and process-level understanding of various Earth System dynamics and ecosystems. This robust community may take the form of cross-agency partnerships, stakeholder engagement, and other collaborative networking opportunities where science communication and mentorship are critical for building credence, catalyzing further participation and interest in science, and developing creative new solutions to address future carbon management needs and GHG mitigation monitoring challenges (e.g., negative emissions). Bridging the gap between data modalities and societal relevance requires developing partnerships and prioritizing criteria for unified spaceborne and in-situ observing systems and modeling frameworks.

Adaptable architectures should be constructed in flexible, modular, and scalable frameworks that leverage cloud computing resources, employ AI/ML algorithms to reconcile and automate data inconsistencies, and parallelize data preprocessing, harmonization, and assimilation workflows. These architectures should extend and enable applied methods and modern data products including real-time climate risk assessment tools and incentivizing sustainable practices with carbon and ecosystem services. These approaches not only aim to improve precision and reduce uncertainty, but also build trust and credibility when translating data into actionable, policy-relevant insights. Science communication may be realized through community-based efforts that fundamentally affect and govern societal value including citizen science programs, storytelling with data, interactive models, and pilot study demonstrations. Involving stakeholders, policymakers, and end-users in project formulation and mission progress often ensures deadlines, deliverables, and outputs are both relevant and impactful. Moreover, constructing climate risk assessment systems rooted in scientific rigor not only empower but strengthen policymakers and stakeholders ability to make well-informed decisions grounded in a transparent multimodal approach to better understanding the Earth System. To advance and apply these recommendations in the interest of bolstering a unified GHG observing system with actionable recommendations and societal value for a variety of ecosystems undergoing rapid change, we turn our focus to specific recommendations structured around research efforts within the Arctic, and tropics for demonstration purposes.

10.2. Examples of field campaign coordination

The Arctic is experiencing an amalgamation of complex feedback mechanisms (i.e., permafrost- carbon feedbacks) and amplified warming patterns signified by accelerated permafrost degradation, rapid and persistent carbon release, and wildfires. To address this challenge, expanding permafrost degradation monitoring efforts and improving CO_2 and CH_4 detection across the Circumarctic are crucial to deploying novel and sound methodologies that represent both landscape characterizations and subsurface dynamics. Coordinating synergistic field campaigns and strengthening long-term monitoring partnerships will address seasonal variability. End-user services should focus on developing Arctic-targeted decision support tools, such as near-real-time (NRT) product delivery of active layer thickness (ALT) maps and methane hotspots. Integrating in-situ, remote sensing, and model data through data assimilation and AI/ML frameworks will enhance predictive ESMs and improve understanding of permafrost-carbon feedback.

Tropical regions are characterized by high uncertainty in CH_4 and CO_2 flux dynamics and rapid deforestation, forest degradation, and shifting disturbance regimes (e.g., drought and fire) that lead to canopy loss and carbon stock depletion. Deploying Lidar and SAR platforms, such as GEDI and UAVSAR/NISAR, to monitor biomass and deforestation rates will improve understanding of these dynamics; enhancing GHG monitoring with TROPOMI and OCO-3 will further supplement these efforts. Strengthening local monitoring networks, particularly in forested and peatland areas of Amazonia, the Congo Basin, and Southeast Asia, is essential. End-user services should include co-developed GHG monitoring platforms, accessible inventory tools, and enhanced forest models that integrate disturbance-recovery cycling with Lidar, radar, and flux data through data assimilation. These improvements will refine forecasts of tropical carbon-climate feedbacks (Carroll et al., 2025b).

10.3. National and international coordination

Developing an operational carbon and modeling system to address scientific and societal needs requires substantial coordination between federal, state, academic, and NGOs within the U.S., as well as internationally through entities like the WMO G3W, UNEP, and CEOS. Through national efforts such as the U.S. Greenhouse Gas Center, NASA can continue to play a leadership role in advancing the synthesis of these data to generate more-accurate carbon information and the adaptation of that data to better support GHG decision makers. The operational continuity and open-data policy of the Copernicus programme, combined with high-resolution CO_2 and NO_2 measurements from CO2M, will provide a sustained, internationally-accessible observational backbone that can anchor and harmonize global GHG monitoring efforts, supporting treaty verification, national inventory reporting, and coordination across complementary satellite missions such as GOSAT and OCO-3.

One example of large-scale efforts in support of carbon cycle data synthesis and scaling are NASA terrestrial ecology field campaigns, in which multi-disciplinary teams examine how Earth's terrestrial ecosystems interact with the atmosphere and hydrosphere, and the roles they play in biogeochemical cycling. Most recently, these include the Arctic-Boreal Vulnerability Experiment (ABoVE; 2015–2024) and the Large Scale Biosphere-Atmosphere Experiment in Amazonia (LBA; 1998–2011). These campaigns enable coordinated data collection at multiple scales spanning ground measurements, eddy covariance flux towers, drone and aircraft, and satellite acquisitions to improve the calibration and validation of satellite retrievals, as well as algorithm and product development. Two projects were recently scoped as possible future Terrestrial Ecology field campaigns: ARID (Adaptation and Response in Drylands; Reed et al., 2025) and PANGEA (PAN tropical investigation of bioGeochemistry and Ecological Adaptation, Ordway et al., 2025). Both have strong potential to advance global carbon cycle understanding and modeling and monitoring capabilities through coordinated multi-sectoral research and applications.

11. Concluding remarks and recommendations

Greenhouse gas emissions continue to grow and impact climate, humans, ecosystems, and natural resources worldwide. The time remaining to decarbonize and achieve net zero emission goals and stabilize global climate is running short. The current GHG observing system, focused mainly on short-lived inquiry driven scientific missions, has improved our understanding of global carbon cycle change, but has fallen short in providing actionable and policy relevant carbon flux and stock information needed to reduce emissions and enhance sinks in support of carbon management efforts. Tracking and mitigating GHG emissions requires a pivot to operational monitoring, with increased focus on frequent, long-term, and closer-in-time monitoring of human based carbon removal efforts and climate driven losses related to extreme weather and carbon climate feedbacks. Critical to this system is the ability to monitor diffuse carbon fluxes at intermediate spatial scales (10–1000 km) in order to tie together local information from surface networks and global information from column integrated GHG data to meet multi-scale carbon management needs.

As the foundation of this system, we envision dedicated measurements of GHG partial columns in the lower and upper troposphere to fuse information across scales from surface and satellite EO data and integration of top-down/bottom-up analyses to link process understanding to global assessment. Existing EO data from surface (towers) and satellite (plume monitors, flux and biomass mappers) observing systems are already providing baseline information at local ($<$ 1 km) and global ($>$ 100–500 km) scale necessary for carbon management. The addition of frequent (daily to weekly) GHG partial columns from airborne and satellite constellations across key regions, ongoing collection and harmonization of Lidar and SAR data for more accurate mapping of above ground biomass and monitoring of vegetation growth and disturbance, and expanded surface-data networks for oceans, land, and aquatic ecosystems to fill sampling gaps, offers feasible, near-term opportunities for end-to-end biomass mapping, enhances detection of weaker emissions and growth patterns at intermediate scales (1–100 km) across mixed landscapes, and ultimately more actionable information that facilitates efforts to increase carbon storage and reduce emissions and leaks.

Long term operational monitoring of GHGs via low earth orbit (LEO) or geostationary orbit (GEO) will be needed for continuity over decades. A single instrument in geostationary orbit can help meet the minimum requirement for frequency and longevity to support national resilience (e.g., to weather disasters) and maximize opportunities for action (given low latency GHG information). A constellation of two satellites, for example including a multi-spectral sounder in GEO to monitor at regional scale, and an active instrument in LEO to monitor global ecosystems and address sampling challenges in cloudy and dark regions, will facilitate a smoother transition to NZE as both expected and unexpected carbon sources are carefully monitored.

Continuity of any new observing system with existing observations will be critical for addressing long-term monitoring needs (e.g., Fig. 1) and for ensuring that carbon management efforts related to emissions mitigation and carbon dioxide removals are effective. Carbon-climate feedbacks arising from natural processes such as permafrost thaw, tropical forest dieback, reduced ocean uptake, and intensifying climate extremes are already compromising existing carbon sinks in the land and ocean, and have significant potential to amplify with continued warming and disrupt carbon management efforts (Carroll et al., 2025b). Detecting and quantifying these dynamics requires sustained observations into the future, as well as backward compatibility as improvements to instrumentation and observing strategy are introduced. Validation programs (e.g., Wunch et al., 2011; Frey et al., 2019) that span multiple satellite missions will also be needed.

The use of advanced carbon cycle models and integrated analyses of surface and spaceborne data with inventory estimates will help maximize the actionable value of EO data (e.g., Fig. 3). As detailed in this paper and summarized in Parazoo et al. (2025), inverse analyses provide a direct link between GHG data and surface fluxes, with partial columns bridging science and observational gaps between local and global data. Carbon cycle data assimilation systems can boost mechanistic insight delivered by processed based models, inform assessment of past changes, and improve projections of future scenarios (Carroll et al., 2022; MacBean et al., 2022; Reichstein et al., 2022). Machine learning, artificial intelligence, and statistical methods can facilitate more effective use of multi-scale EO data by enabling gap filling in space and time, upscaling of discrete surface measurements to larger regions, downscaling of spatially integrated datasets to management scales, and identification of process controls (McNicol et al., 2023).

In conclusion, we advocate for a coordinated space-based system for monitoring carbon and biomass that: 1) combines partial-column retrievals to bridge local and global scales, 2) provides fine enough spatial resolution to capture signals between cloud cover, and 3) harmonizes biomass products to enable wall-to-wall global forest mapping. This system must be deeply integrated with surface observation networks to maintain consistent long-term records, and should be designed with forward compatibility in mind so that new data streams can be readily assimilated into inverse models and used to constrain key surface carbon processes. By synthesizing existing and emerging EO data with ground-based inventories through advanced top-down and bottom-up frameworks, such a system would be well positioned to meet the evolving and diverse needs of carbon management stakeholders and decision-makers.

List of Key Acronyms

AFOLU	Agriculture, Forestry and Other Land Use
AI	Artificial Intelligence
ATL	Active Layer Thickness
API	Application Programming Interface
BL	Boundary Layer
CDAS	Carbon Cycle Data Assimilation Systems
COCCON	COllaborative Carbon Column Observing Network
CO2M	Copernicus Anthropogenic Carbon Dioxide Monitoring mission
CDR	Carbon Dioxide Removal
DOF	Degrees of Freedom

DS	Decadal Survey
EF	Emission Factors
EO	Earth Observation
FT	Free Troposphere
GCP	Global Carbon Project
GHG	Greenhouse Gas
GST	Global Stocktake
iFTS	Imaging Fourier Transform Spectrometers
IPDA	Integrated Path Differential Absorption
KGM	Knowledge Guided Machine Learning
LT	Lower Troposphere
MDPS	Multi-Mission Data Processing Systems
MCL	Methyl Chloroform
ML	Machine Learning
NbCS	Nature-based Climate Solution
NDC	Nationally Determined Contributions
NFIs	National Forest Inventories
NIR	Near Infrared
NRT	Near Real Time
NWP	Numerical Weather Prediction
OH	Hydroxyl Radical
PoR	Program of Record
TCCON	Total Carbon Column Observing Network
TCRE	Transient Climate Response to Cumulative Carbon Emissions
TIR	Thermal Infrared
UT	Upper Troposphere
VOD	Vegetation Optical Depth
ZEC	Zero Emissions Commitment

Open research

The data used in the model simulation to derive flux footprints and uncertainty for partial and total GHG column analysis in Fig. 3 will be made available in an open data repository at the Jet Propulsion Laboratory through the JPL Open Repository (JOR): https://dataverse.jpl.nasa.gov/dataverse/jor

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.

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Data availability

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

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