

N. Parazoo and D. Carroll are co-first authors.

Peer Review The peer review history for this article is available as a PDF in the Supporting Information.

Key Points:

- Managing carbon stocks under climate forcing requires a global view of local and regional scale processes
- Near surface partial column Greenhouse Gas data can improve the ability to resolve carbon fluxes at assessment and management scales (<100 km)
- A carbon observation system providing actionable information should integrate partial columns with sustained Earth observations and models

Supporting Information:

Supporting Information may be found in the online version of this article.

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Citation:








Parazoo, N., Carroll, D., Abshire, J. B., Bar-On, Y. M., Birdsey, R. A., Bloom, A. A., et al. (2025). A U.S. scientific community vision for sustained earth observations of greenhouse gases to support local to global action. *AGU Advances*, 6, e2025AV001914. <https://doi.org/10.1029/2025AV001914>

Received 12 JUN 2025

Accepted 10 OCT 2025

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A U.S. Scientific Community Vision for Sustained Earth Observations of Greenhouse Gases to Support Local to Global Action

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Abstract Managing carbon stocks in the land, ocean, and atmosphere under changing climate requires a globally-integrated view of carbon cycle processes at local and regional scales. The growing Earth Observation (EO) record is the backbone of this multi-scale system, providing local information with discrete coverage from surface measurements and regional information at global scale from satellites. Carbon flux information, anchored by inverse estimates from spaceborne Greenhouse Gas (GHG) concentrations, provides an important top-down view of carbon emissions and sinks, but currently lacks global continuity at assessment and management scales (<100 km). Partial-column data can help separate signals in the boundary layer from the overlying atmosphere, providing an opportunity to enhance surface sensitivity and bring flux resolution down from that of column-integrated data (100–500 km). Based on a workshop held in September 2024, the carbon cycle community envisions a carbon observation system leveraging GHG partial columns in the lower and upper troposphere to weave together information across scales from surface and satellite EO data, and integration of top-down/bottom-up analyses to link process understanding to global assessment.

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Plain Language Summary The iconic CO₂ data set initiated by C.D. Keeling at Mauna Loa, Hawaii has been instrumental in our understanding of the global carbon cycle and underpins policy efforts aimed to mitigate carbon emissions and climate change impacts. As our knowledge of the carbon cycle grows, it becomes increasingly critical to acquire information at finer spatial scales to better understand the complexity of carbon movement across the ocean and land. At the same time, policies that seek to mitigate carbon emissions benefit from observations to guide actions at city-to-national scales. The scientific community has developed a suite of carbon observations spanning multiple scales, demanding traceability, integration, and global context. Satellite measurements can fill this role but rely on further efforts to link with natural and anthropogenic processes. In this position paper, carbon cycle scientists call for an integrated carbon observing system leveraging near-surface partial-column Greenhouse Gas data—capturing the atmosphere closest to forests, cities, and oceans—to better resolve finer spatial scales (<100 km) where key carbon cycle processes and management decisions occur. This system should be anchored by ground observations that are not dependent on any single nation-state to provide internationally recognized carbon emissions products for policy and planning.

1. Background

Due in large part to international efforts to enact climate policy, advance technology, shift from coal to gas, and expand the use of renewable energies, the annual growth in global anthropogenic CO₂ emissions 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 Greenhouse Gas (GHG) leaks from oil and gas facilities (e.g., Cusworth et al., 2022). Although we are still far from the sharp and sustained reductions needed to limit GHG induced temperature change, these efforts represent significant progress and underscore the utility of targeted and sustained carbon management at local to global scales. Collective efforts to be considered include mitigation through management of GHG emissions as well as removals, and adaptation to prepare for and address the consequences of climate extremes on our planet's natural resources. These are critical strategies for anticipating, controlling, and planning for the accelerating effects of climate change on ecosystems, human health, and global economies. To provide scientific guidance on GHG observing system needs and strategies for the next Decadal Survey, representatives from carbon cycle biomass and flux communities across United States government agencies and academic institutions met in September 2024 to discuss state of knowledge and opportunities for progress and offer a vision for implementation of an actionable system linking new and existing information across scales.

2. Monitoring GHGs to Support Carbon Management

GHG observing systems have been tracking global CO₂ concentrations since the late 1950s, with this data essential to carbon management efforts. GHG monitoring efforts were pioneered by the Scripps CO₂ Program and then complemented by high-precision analysis of CO₂ mole fractions through international networks (see Jacobson et al. (2023) for list of networks). These monitoring efforts are ongoing and have been augmented by space-based GHG sensors, which together have been used to infer fluxes of carbon by increasingly sophisticated methods that support attribution to various processes, and rapidly refine our understanding of emissions from point sources and net exchanges over land and ocean regions. Likewise, spaceborne biomass observing systems have been developed together with data fusion methods to monitor changes in a key storage compartment, carbon storage in vegetation, for the past two decades (Duncanson et al., 2019).

National inventory reports quantify sources of anthropogenic emissions and removals by sinks of GHGs using good-practice methodologies developed by the Intergovernmental Panel on Climate Change (IPCC), based on “bottom-up” inventories. The IPCC Taskforce on Inventories also acknowledges the value of “top-down” approaches for quality control and assurance (IPCC, 2019). Operational GHG monitoring systems that leverage bottom-up inventories and top-down inferences can offer more accurate and granular GHG information to support carbon management and decision making across multiple spatial (ecosystem to global) and temporal (weekly to decadal) scales (e.g., Ogle et al., 2015; NASEM, 2022). Yet to be useful to a wide range of local, national, and international stakeholders (e.g., policymakers, multi-national corporations, financial markets) with interest in carbon management, carbon flux monitoring and attribution must capture diverse spatiotemporal scale needs for carbon cycle science (Figure 1).

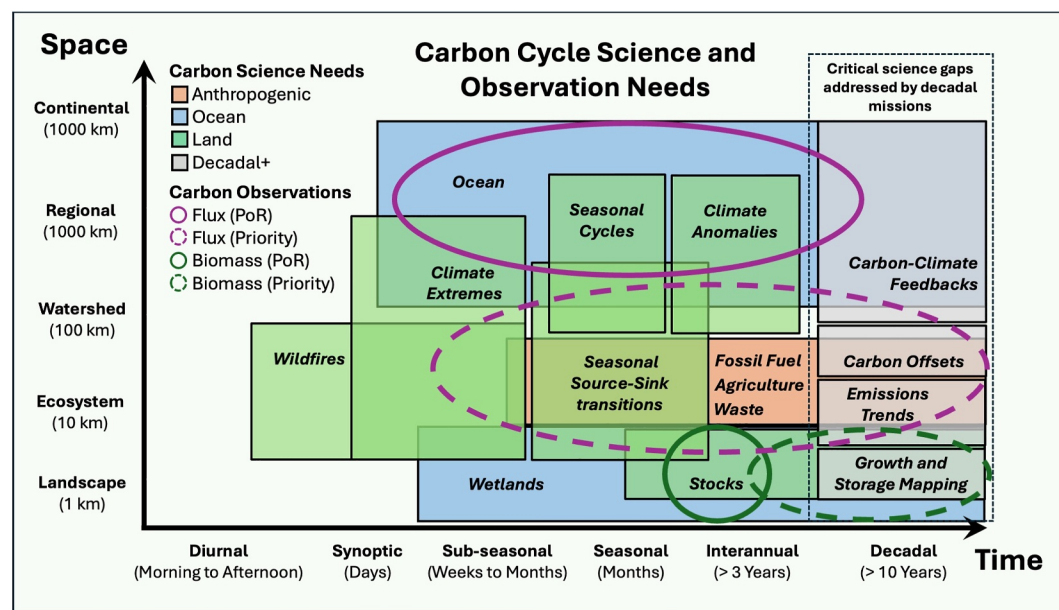


Figure 1. Carbon Cycle Science and Observation Needs. Diverse carbon cycle science needs span multiple time (x-axis) and space (y-axis) scales across land (green shading), ocean (blue shading), and fossil (orange shading) sectors. Science needs addressed by the current and planned carbon flux and biomass Earth Observation (EO) program of record (PoR; purple and green, respectively) are depicted by the solid circle. Key EO science gaps exist at 1–100 km spatial scale spanning sub-seasonal impacts of climate extremes and wildfires, interannual change and biomass, long term changes in growth, storage, and emissions, and carbon-climate feedbacks and tipping points (gray shading). Future GHG and biomass observing systems (e.g., dashed circles) will provide important benefits to carbon management efforts.

3. Carbon Cycle Science Gaps

The global carbon cycle features a range of natural and anthropogenic processes in the land, ocean, and atmosphere which continuously store and transfer carbon between pools. 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 fine scales (e.g., of an individual plant). However, our ability to detect, quantify, and disentangle natural and anthropogenic emissions and their spatiotemporal distribution, and predict the range of responses to environmental and socioeconomic factors at scales larger than individual plots, remains limited (Randerson et al., 2025).

Global fossil fuel emissions have stabilized at record highs and are relatively well known at coarse (national and annual) scales. Uncertainty increases at sub-national and sub-annual scales as emissions become decorrelated from activity levels, and assumptions are made to disaggregate large scale estimates (Hogue et al., 2016; Oda et al., 2019, 2021, 2023). Long term monitoring of anthropogenic emissions at finer spatial scales (1–50 km) can facilitate detection of trends and dominant sources across fossil, agricultural, and waste management sectors (orange shading, Figure 1).

The terrestrial biosphere is affected by ongoing losses and uptake of carbon, including major fluxes associated with Land Use Land Cover Change and ecosystem management. Quantifying changes and attributing them to natural and human causes is difficult because the pattern of gain and loss varies at local scales. A major challenge lies in resolving discrepancies in national inventory-based estimates of land carbon stocks and fluxes with EO-based estimates (Grassi et al., 2023). Uncertainties in land flux and stock are the largest (by percentage) of any carbon pool (Friedlingstein et al., 2024). Future changes due to several land carbon-cycle feedbacks increase this complexity and reinforce the need for a long-term monitoring system. Monitoring the evolution of carbon stocks and fluxes within the Agriculture, Forestry and Other Land Use (AFOLU) sector (IPCC, 2022), and quality of emission credits, offsets, and leakages generated in forest and agricultural systems (Badgley et al., 2022; Cullenward & Victor, 2020; Silva & Nunes, 2025), at spatial scales of 1–100 km and sub-seasonal to decadal time scales, is a key priority for land ecosystems (green and gray shading, Figure 1).

The ocean has absorbed additional carbon equivalent to 37% of cumulative fossil fuel emissions since 1850, and $2.9 \pm 0.4 \text{ Pg C yr}^{-1}$ (26%) from 2013 to 2022 (Friedlingstein et al., 2024). Like terrestrial ecosystems, forced and internal climate variability drive significant interannual variability in carbon exchange (Crisp et al., 2022; Fay et al., 2023; Gruber et al., 2023; McKinley et al., 2017). Unlike the multiplicity of drivers for ecosystem carbon change, ocean uptake of anthropogenic carbon is due to the strong forcing from growing atmospheric CO_2 partial pressure, and the spatial integration of compensating regional patterns leads to more consistent global values (Fay & McKinley, 2021; McKinley et al., 2020). Better estimates require both improvements to models and data to better capture spatial variability (Gloege et al., 2021; Hauck et al., 2023; Heimdal & McKinley, 2024). Sustaining and expanding global ocean EO data at scales of 10–1,000 km would reduce uncertainty in the ocean carbon sink (Peters et al., 2017) (blue shading, Figure 1).

4. Program of Record for Carbon Flux and Stock

The Committee on Earth Observation Satellites (CEOS) and the World Meteorological Organization track the world's space-based EO program of record, which shows increasing coverage of major components of the global carbon cycle. Most of these observations began within the last 10 years, and will continue to provide detailed observations into the future, through global (Flux Mappers: OCO-2/3, TROPOMI, GOSAT-2, GOSAT-GW, SCIAMACHY, IASI, CO2M, MicroCarb) and local (Plume Monitors: GHGSat, EMIT, CarbonMapper) GHG gradients, terrestrial biomass (GEDI, ICESat-2, NISAR, ALOS-4), and key controls related to ecosystem properties (Landsat-NEXT, LSTM, CHIME, SBG, ROSE-L, CIMR), ocean color (PACE, GLIMR), ocean properties (SWOT, Sentinel-3/6, CRISTAL).

Ground-based measurements focus on monitoring and understanding carbon flux and related properties at discrete global locations in land, ocean, and wetland regions. For land regions, these data include eddy covariance networks (FLUXNET, FACE) and forest plot inventories for flux, biomass, and soil carbon (Baldocchi, 2020; Batjes et al., 2020; Pan et al., 2024). For the ocean, monitoring platforms include ship-based approaches, eddy covariance (Dong et al., 2024), Saildrones (Sutton et al., 2021), autonomous vehicles, and ARGO/BGC-Argo profiling floats (Claustre et al., 2020). Wetland-based monitoring networks (Buskey et al., 2015) use eddy covariance towers and high-resolution drone surveys (Ganju et al., 2024).

Plume monitors and flux mappers cover spatial scales of intense point source emissions (<1 km) and weaker, spatially distributed (diffuse) fluxes (100–500 km), respectively, and temporal scales of weeks to years. Biomass missions constrain carbon stocks at landscape to ecosystem spatial scale (0.1–10 km) and annual time scale (Figure 1). Spaceborne flux and biomass data are complemented by more detailed constraints of local processes (0.1–5 km) from ground-based networks (not shown in Figure 1).

5. Carbon Cycle Observation Gaps

The current GHG observing system, focused nominally on short-lived (1–3 years), inquiry-driven scientific missions, has improved our understanding of global carbon cycle change, but has fallen short in providing actionable carbon flux and stock information. The key observation gaps for effective carbon cycle assessment and management under global climate forcing occur at intermediate spatial scales (10–100 km) for carbon flux and decadal time scales for both carbon flux and biomass. At these scales, ground-based measurements are spatially sparse, satellite GHG data is limited in terms of surface sensitivity, and global long-term continuity is challenging. We stress that resolving these scales is critical for long-term monitoring of carbon storage, leakage, and emissions from large forest conservation projects (e.g., Envira Amazonia Project; <https://www.reforestation.com/en/projects/1722>), reforestation efforts (e.g., Silva & Nunes, 2025), carbon storage and yield in croplands (Foster et al., 2025), carbon reduction policies in cities (Duren & Miller, 2012), as well as for informing process-based modeling and management impacts (Foster et al., 2025).

5.1. Carbon Flux Gaps

Three key challenges limit the use of existing GHG missions to provide actionable information at intermediate spatial scales. The first challenge is the focus on inquiry-driven fundamental science questions and relative lack of attention to operational monitoring. While research-driven missions are necessary to advance scientific understanding to inform operational aspects, they are insufficient in the absence of long-term, low latency, open and transparent information needed to monitor whether or not mitigation efforts are on track. Copernicus is taking

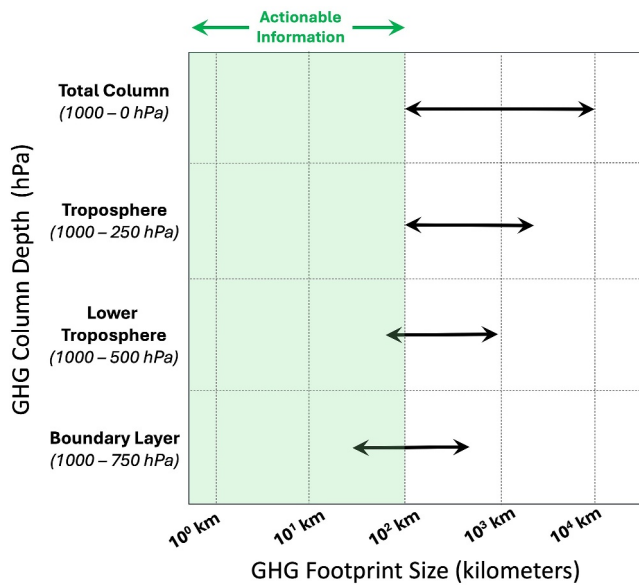


Figure 2. Concept Diagram Illustrating the Sensitivity of Surface CO₂ Fluxes to the Vertical Depth of Atmospheric CO₂ Concentration. The mean area of influence of surface carbon flux on atmospheric CO₂ increases with vertical integration depth. Boundary layer concentrations are more sensitive to local influences, and thus have a smaller mean footprint and increased actionable information (green shading). Column-integrated measurements, representing the entire atmosphere including the boundary layer, are sensitive to long-range transport, and thus have reduced sensitivity to underlying surface exchange. The variability (arrows) also increases with depth due to variable influence of vertical and horizontal mixing.

retrievals (e.g., Kuai et al., 2013; Kulawik et al., 2017; Kuze et al., 2022), enable separation of information in boundary layer air near the surface (1,000–750 hPa) from the overlying atmosphere (<750 hPa) (Gatti et al., 2021; Sarmiento & Wofsy, 1999). These separate pieces of vertical information can greatly increase sensitivity to local and regional fluxes (e.g., Carroll et al., 2025), and advance closure of science gaps in land, ocean, and anthropogenic sectors at sub-100 km scale (Figures 1 and 2).

5.2. Biomass Gaps

Ecosystem storage of carbon is crucial for most carbon management schemes and critical to understanding feedbacks from changing CO₂ and climate. Global above-ground biomass (AGB) varies from under 100 MgC ha⁻¹ in low carbon-density ecosystems (e.g., grasslands, temperate forests) up to 300 MgC ha⁻¹ in high carbon-density tropical forests (Xu et al., 2021). Detecting global forest biomass change requires accuracies of ≤20 MgC ha⁻¹ at hectare scale resolution (Healey et al., 2023). Spaceborne Lidar altimetry (GEDI, ICESat-2) and Synthetic Aperture Radar (SAR) (ALOS) are providing our best estimates of AGB, but uncertainties remain due to difficulty sampling through clouds and saturation in high biomass areas, respectively, and limited calibration and validation sites especially in the tropics. Lidar can accurately measure canopy height and volume without saturation, but with limited coverage (Magruder et al., 2024). Recent missions, such as NISAR (Siqueira et al., 2021) and BIOMASS (Quegan et al., 2019), will improve global mapping, accuracy (~20 Mg/ha; NISAR, 2019), and tropical coverage, but uncertainties related to SAR and Lidar sampling of dense forest and cloudy regions remain. Combining the strengths of Lidar altimetry's vertical precision with SAR cloud and canopy penetration capabilities through biomass harmonization (Hunka et al., 2023), combined with enhanced reference calibration and validation data sets (Duncanson et al., 2019), can help reduce the large uncertainties persisting in land carbon flux estimates to enable high-resolution biomass mapping at scales capturing forest management and natural disturbance.

steps to address operational GHG needs through future missions such as CO2M, which will monitor global human emissions. Meeting actionable information needs of stakeholders mandates sustained coordination of inquiry- and operational- driven missions.

Another challenge for GHG missions relates to the frequency and spatial resolution at which GHG data is collected. For example, low sampling frequency (~weeks) can limit detectability of disruptions to carbon budgets and markets related to weather extremes, while coarse footprints (1–5 km) can limit sampling between clouds especially in regions of persistent cloudiness such as the humid tropics (e.g., Frankenberg et al., 2024). Higher-frequency data can more accurately inform risk assessment of value to insurers and carbon markets.

A third challenge is the focus on column-integrated GHGs, which integrate over large spatial (>1,000 km, Figure 2) and temporal (~weekly) scales. While essential for disentangling large-scale variations in natural carbon fluxes from steadier trends in human emissions (Pandey, 2025), the use of column-integrated data alone can smooth out sectoral-level processes where management decisions occur, leading to poor detection of diffuse fluxes within urban, rural, agricultural, and forested landscapes. Top-down methods can help optimize diffuse fluxes down to 100–500 km spatial scale globally through inverse modeling (e.g., Byrne et al., 2023; Qu et al., 2021) and point and urban emissions locally through Gaussian plume modeling (Moeini et al., 2025) by leveraging column data with covariate information from other satellites, towers, inventories, models, and optimal estimation techniques.

Breaking the 100–500 km flux optimization barrier globally for diffuse fluxes requires new methods with increased surface sensitivity. Airborne and spaceborne vertical profiles, derived from in situ sampling and partial-column

6. Linking Scales With Partial Columns

We envision a carbon management system anchored by (a) partial column data in the lower and upper troposphere to fuse information across scales from surface and satellite EO data and (b) 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 harmonized biomass and partial-column data leveraging existing methods offers feasible, near-term opportunities for end-to-end biomass mapping, increased surface flux sensitivity at intermediate scales (1–100 km), and ultimately more actionable information that facilitates efforts to increase carbon storage and reduce emissions and leaks. Continuity of new observations with existing observations will be key to address long-term monitoring needs, and require backward compatibility when improvements are introduced; validation programs (e.g., Frey et al., 2019; Wunch et al., 2011) 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 can help maximize the actionable value of EO data. Inverse analyses provide the 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 of Dynamic Global Vegetation and Ocean Biogeochemistry Models (DGVMs and OBM), 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 and artificial intelligence can facilitate upscaling of surface data through fusion with remote sensing data to fill gaps and identify process controls (McNicol et al., 2023).

We therefore recommend development of a space-based carbon and biomass observing system with (a) partial columns providing increased surface sensitivity linking local-to-global scales, (b) sufficient spatial resolution to observe between clouds, (c) harmonized biomass providing wall-to-wall mapping of global forests, (d) strong integration with surface networks to ensure consistent long-term records, and (e) forward planning to ensure backward compatibility and streamlined assimilation of such data in inverse models to provide constraints on the key surface processes. Such an actionable system that integrates existing and new EO data and inventories using advanced top-down and bottom-up analyses can help address the diverse and shifting needs of carbon management stakeholders.

List of Acronyms:

AGB	Above-ground Biomass
AFOLU	Agriculture, Forestry, and Other Land Use
CCDAS	Carbon Cycle Data Assimilation Systems
CEOS	Committee on Earth Observation Satellites
DGVM	Dynamic Global Vegetation Model
EO	Earth Observation
GHG	Greenhouse Gas
IPCC	Intergovernmental Panel on Climate Change
LULCC	Land Use Land Cover Change
OBM	Ocean Biogeochemistry Model
POR	Program of Record
SAR	Synthetic Aperture Radar

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

Data were not used, nor created for this research.

Acknowledgments

The workshop was funded as an unsolicited proposal (Proposal #226264: In support of “Carbon Stocks Workshop: September 23–25, 2024”) by the U.S. Greenhouse Gas Center, Earth Science Division, NASA. We acknowledge Anna Karion for participating in the workshop and the many constructive conversations. DC acknowledges support from the NASA Carbon Monitoring System (CMS) program. RKB was supported in part by the Resnick Sustainability Institute at Caltech. AF acknowledges funding from the NASA ECOSTRESS Science Team. NL is grateful for funding from NSF (OCE-1752724). GM acknowledges funding from NASA CMS (NNH20ZDA001N). HN and BAG acknowledge support from appointments to the NASA Postdoctoral Program at the Jet Propulsion Laboratory, California Institute of Technology, administered by Oak Ridge Associated Universities under contract with NASA. The findings and conclusions in this publication are those of the author(s) and should not be construed to represent official USDA or U.S. Government determination or policy. The research was carried out at the Jet Propulsion Laboratory, California Institute of Technology, under a contract with the National Aeronautics and Space Administration (80NM0018D0004). Any use of trade, firm, or product names is for descriptive purposes only and does not imply endorsement by the U.S. Government. © 2025. All rights reserved.

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