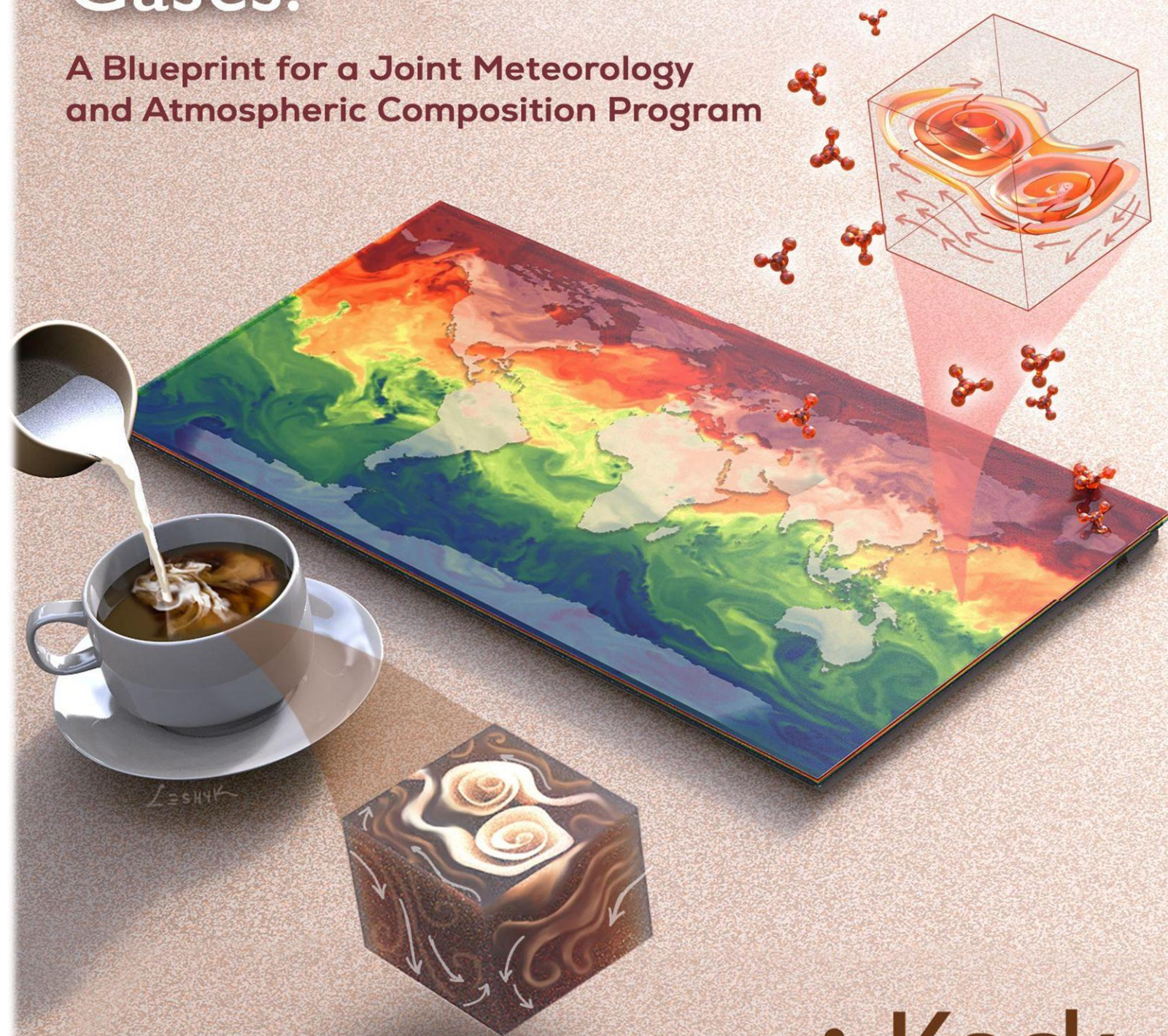


Tracing Greenhouse Gases:

**A Blueprint for a Joint Meteorology
and Atmospheric Composition Program**





A Blueprint for a Joint Meteorology and Atmospheric Composition Program

November 2025

Study Workshop: October 7-11, 2024

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Workshop Participants



Group photo of the participants of the Forging Community Consensus for an Integrated Greenhouse Gases and Winds Program study workshop, held October 7-11, 2024, at the Keck Institute for Space Studies at the California Institute of Technology. Image credit: Keck Institute for Space Studies/Harriet Brettle

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1. EXECUTIVE SUMMARY

For greenhouse gas (GHG) observations to more effectively inform climate management strategies, we must be able to better identify the timing, location, and magnitude of surface emissions and removals. Making atmospheric composition data actionable requires improved traceability to surface fluxes. For this, we need better observation of the vertical distribution of trace gases and better modeling of vertical atmospheric mixing. Uncertainty in vertical transport and mixing has been especially problematic because of two factors: (1) long tracer lifetimes can lead to accumulation of vertical mixing errors over time and space, and (2) covariance of vertical mixing with surface fluxes confounds attribution of trace gas data to surface fluxes. These problems are exacerbated by the presence of clouds and wind shear, which can obscure the origin of trace gases.

A new generation of models and space-based GHG and wind remote sensing techniques is emerging. These tools show promise for observing and simulating the small scales at which vertical mixing occurs, with near-global coverage. Spaceborne GHG missions will continue to close spatial and temporal sampling gaps, increasingly target collocated species (CO_2 , CH_4 , CO , NO_x), and vertical gradients (via multi-spectral lidar and spectrometers) for improved sectoral attribution of carbon emissions and removals. Wind missions leveraging passive and active techniques to track the motion of cloud and trace gas spatial features, cloud liquid and ice hydrometeors (radar and lidar), and air/particulates (lidar) are improving our ability to track vertical and horizontal motion within and around clouds. High-resolution numerical weather prediction and climate models and machine learning-driven forecasting that resolve deep convection and permit shallow convection are improving the statistics of vertical mixing at regional scales. The combination of wind and GHG observations with high-resolution models will strengthen our knowledge of GHG mixing, connecting surface exchange to atmospheric abundances.

To provide scientific guidance on how to bring these modeling and observing tools together for more accurate GHG and air quality climate data, the Earth science community needs to move beyond single instrument teams to tackle integrated science challenges. We recommend the development and coordination of a joint meteorology and atmospheric composition program, whose goal is to vastly improve GHG source and sink quantification while simultaneously advancing our understanding of vertical atmospheric mixing.

We envision a three-tiered model-observation integration approach to reduce uncertainty in vertical mixing based on existing and future observations:

- **Diagnosis**—Comparing models to observations to identify process uncertainty,

- **Optimization**—Assimilation of observations into models to optimize parameters and state, and
- **Prediction**—Forward and inverse simulation using calibrated model ensembles.

A key component of this approach is the development of testbeds to inform vertical mixing, building on coordinated programs such as the European Union-led Carbon Atmospheric Tracer Research to Improve Numerics and Evaluation (CATRINE) project. These recommendations are supported by the National Academies Earth Science Decadal Survey Midterm findings to expand collaboration opportunities, and to more actively engage the modeling communities.

2. INTRODUCTION: PROVIDING ACTIONABLE INFORMATION FROM GRIDDED SURFACE FLUXES

The science and stakeholder communities need to clearly understand how gases in Earth's atmosphere exchange with the surface, are modified by chemistry, and are redistributed by the winds to guide climate policies and to understand the changing carbon cycle. To provide guidance on how to bring modeling and observing tools together for actionable greenhouse gas (GHG) data, representatives from the GHG and Winds communities convened in October 2024 for a five-day workshop. Our discussions led to the conclusion that the Earth Science community needs to move beyond single-instrument teams to tackle integrated Earth science problems, including those related to the carbon cycle and air quality. We recommend the development and coordination of a joint meteorology and atmospheric composition program whose goal is to vastly improve GHG source and sink quantification while simultaneously advancing our understanding of vertical air movement. In this report, we provide a framework by which we can classify actionable problems according to relevant spatial scale. We highlight areas that need particular attention and outline what effective cross-disciplinary community support could look like.

2.1 BACKGROUND

The global carbon cycle encompasses the interactions among physical, biological and human-driven processes within the Earth system that leads to flows of carbon between land, ocean, and atmospheric reservoirs. Natural flows remain in quasi-steady state in the absence of external forcing. Humans have perturbed the natural cycle through fossil fuel combustion, which has led to a rapid and massive redistribution of carbon from underground, where it is stored in solid, liquid, and gaseous state, to the atmosphere, where it is stored in gaseous state

and acts as a GHG. Fossil fuel emissions act as an external force by changing the concentration of carbon dioxide (CO₂) and methane (CH₄) in the atmosphere, affecting the amount of total energy received at the surface. The Earth system is responding to this forcing by creating carbon sinks, which remove a fraction (~50%) of this excess CO₂ through increased storage in the land and ocean (Friedlingstein et al., 2025). The magnitude and sign of this response is dependent on environmental conditions such as air temperature and rainfall, which change daily and seasonally with weather, and also decadal, with changes in energy input from CO₂ and other GHGs.

Managing the excess CO₂ in the atmosphere to meet climate targets involves a combination of activities. We must be able to accurately identify the location, magnitude, and change in surface land-atmosphere carbon flux at different spatial and temporal scales. Advancements in this area serve to distinguish different processes, avoid misattribution, and effectively inform mitigation efforts. This relies fundamentally on measurements of atmospheric CO₂. While these data can be combined with other evidence of carbon cycle change, for example, from biomass and forest inventories, to reveal further information about the carbon cycle at local to global scale (Walker et al., 2021), we must first ensure the reliable and appropriate use of atmospheric CO₂ to estimate carbon flux in time and space and at the scale of interest. Atmospheric CO₂ data are used in two distinct ways in combination with wind data to estimate and monitor changes in the carbon cycle, leading to two vastly different temporal and spatial scales of flux estimation.

On the ecosystem time (hours to decades) and space (leaves to communities, ~1 km) scale, carbon fluxes are estimated using careful and collocated observation of trace gases and winds. Site-level monitoring of carbon fluxes using eddy covariance methods has been occurring across multiple networks at a global scale for decades (Baldocchi, 2020). This approach has been foundational to our understanding of the terrestrial biosphere across climate and ecological space and the response of carbon fluxes to environmental and biological forcing.

On the regional to global scale, carbon fluxes are inferred using in-situ and remote sensing measurements of atmospheric concentrations from ground, airborne, and spaceborne platforms. This approach (described in Chapter 3) uses trace gas concentration measurements at certain times and locations, together with wind information (from data and models) at all times and locations, to infer the spatial and temporal distribution of surface carbon fluxes. For global scale flux estimation (~10,000 km), this approach has leveraged long records of atmospheric concentrations from flasks collected at locations globally since the mid-20th century (Mund et al., 2017). Regional scale carbon fluxes (~100–1,000 km) can be inferred from in-situ records collected more or less continuously at tower and aircraft locations within continental interiors (closer to carbon sources and sinks) since the early 21st century.

While tower data contain information at a global scale, space-based remote sensing has greatly improved our ability to study the Earth's carbon cycle at regional scale (~1000 km) and fill spatial gaps in the in-situ network. The era of space-based remote sensing of atmospheric trace gases was ushered in by the pioneering efforts of the Greenhouse gases Observing SATellite (GOSAT) and NASA's Orbiting Carbon Observatory 2 (OCO-2) in the 2010s. These satellites, which fall into a class of satellite missions called Global GHG Mappers (CEOS-CGMS Joint Working Group on Climate Greenhouse Gas Task, 2024), demonstrated that high-precision, column-integrated CO₂ concentration measurements were not just possible, but highly complementary to in-situ data in terms of spatial coverage, continuity, and linking regional scale processes to global change. Science teams devoted to the application of these instruments have made progress toward improving trace gas retrievals and applying these observations for inference of carbon fluxes over large regions, best demonstrated by the OCO-2 Model Intercomparison Project.¹

Trace gas methods do not currently take full advantage of opportunities enabled by existing atmospheric wind measurements and vice versa. Generally speaking, eddy covariance methods require collocated measurements of atmospheric trace gas and wind fluxes to infer surface carbon fluxes at the same location of the measurements. Trace gas concentration methods also require wind data, but do not necessarily need or benefit from collocated measurements. Incorporating a more focused view of air movement is required to more reliably trace observed concentrations to their point of origin. Conversely, observations of trace gases can provide additional information about air movement useful in studying wind movement.

2.2 COMMUNITY APPROACH

The GHG science community is now at an inflection point: single mission science teams, focused on a single satellite and/or observable geophysical quantity, are no longer sufficient to address our scientific and decision-making needs. Following the continued success of GOSAT and OCO-2, the number and type of space-based GHG observations is growing in response to the variety of scientific needs, most prominently in the anthropogenic GHG emission sector (e.g., Meijer et al., 2022; Thorpe et al., 2023). This brings the promise of a rich set of tools for studying the Earth's sources and sinks of trace gases.

This also brings risk in that more and/or new data does not guarantee improved understanding. We can minimize this risk by following three steps:

¹ https://gml.noaa.gov/ccgg/OCO2_v10mip/

First, we must acknowledge that the Earth Observation program of record is vast and full of untapped information. Critical and proven measurements of atmospheric wind movement and GHGs need to be identified and continued. The drive to explore new technologies should be coupled with attention to maintaining critical observational infrastructure. Likewise, we must consider unmet stakeholder needs. We must connect today's needs with existing capabilities through improved production and delivery of actionable information.

Second, the ability to process new and existing wind and GHG data into actionable information should leverage the expanding suite of sensor platforms and technologies, when possible, to augment capabilities from a single sensor. This includes multi-sensor systems for a single observable at multiple scales. For example, combining Global GHG Mappers optimized for spatially distributed surface carbon fluxes with facility-scale plume monitors with increased sensitivity to more intense point sources (CEOS-CGMS Joint Working Group on Climate Greenhouse Gas Task, 2024) can help better characterize local emissions from background conditions (e.g., (Nelson et al., 2024)). Borrowing from examples provided in Section 2.1, GHG concentration measurements must be combined with reliable information on atmospheric winds to more accurately estimate carbon fluxes at regional to global scale from spatially distributed diffuse carbon sources and sinks.

This brings us to the third step: the ability to accurately monitor and attribute global carbon sources and sinks from Global GHG Mappers requires the use of atmospheric transport models. As stated above and reiterated here, 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 simulation and prediction of trace gas structure. Most likely, GHG and wind observations will remain incomplete (in coverage, frequency, and quality) and require models to fill gaps in space and time, and ultimately link observed concentrations to upwind surface flux through inversion methods (e.g., Byrne et al., 2023). Likewise, models are imperfect. Uncertainty in vertical transport and mixing confounds attribution of trace gas data to surface fluxes (Parazoo et al., 2012) (Schuh et al., 2023). Significant investment in multiple modeling frameworks is needed to keep pace with the growing Program of Record (PoR). Continued development of high-resolution models that resolve deep convection, and combine wind and GHG observations, can strengthen our knowledge of GHG mixing and traceability.

We recommend the establishment of a focused science team with the mission to drive the synthesis of multi-platform atmospheric science. We are calling for a new era of coordinated community science-leveraging expertise from diverse remote sensing and modeling communities. At present, there is no coherent scientific program whose agenda

brings together the growing constellation of space-based measurements of GHGs, winds, and ground-based and airborne counterparts. This team should support development of the emerging suite of space-based carbon cycle science observations and the necessary modeling suite for the timely translation of data to well-informed action.

2.3 CONNECTING INFORMATION WITH ACTION

Inverse modeling is the primary tool for using atmospheric GHG observations from spaceborne and in-situ data to estimate net surface-atmosphere fluxes. Emissions of carbon become entangled into the existing pool of atmospheric carbon through a combination of rapid and gradual mixing by the global atmospheric circulation, eventually causing increases in the concentration of CO₂ globally. Inverse methods must untangle these emissions through observational and process knowledge of the evolving atmospheric state. 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 and understanding of the spatial and temporal scales of flux variability (i.e., a prior) generated by inventories or process-based models (Rodgers, 2000).

The accuracy to which a GHG observation can be traced to a surface emission or removal degrades with time as atmospheric mixing evolves and atmospheric trace gas gradients become more diffuse. The process of estimating GHG sources and sinks is akin to unmixing cream from a cup of coffee—the more time the cream is given to mix with the coffee, the more uniform the coffee appears, and the more difficult it becomes to determine when and where the cream was poured into the cup. Providing accurate GHG flux information, improving our scientific understanding, assessing the efficacy of the carbon cycle, and facilitating mitigation efforts will require: (1) quantifying net fluxes at high spatial and temporal resolutions, and (2) combining dense and frequent observations sensitive to surface process with high-fidelity transport models representing diverse mixing processes.

Currently, estimates from data assimilation and inverse models that leverage atmospheric trace gas observations and atmospheric transport information are not a primary tool for connecting information with organizations taking action on the ground. Local to international bodies are left to rely primarily on trace gas inventories, or “bottom-up” accounting. Many studies have shown that while inventories provide precise information, this information is often not accurate and should take better advantage of the huge amount of additional information available from space-based and in-situ observing platforms that are interpreted “top-down” because they provide an empirical constraint on total emissions (e.g., Task Force on National Greenhouse Gas Inventories [TFI], 2019); Alvarez, 2018; Ciais, 2022; Crisp et al., 2022; Petrescu et al., 2021).

Top-down methods that rely on facility-scale plume monitors (e.g., PRISMA; Cusworth et al., 2021) and targeted or repeated sampling by Global GHG mappers (He et al., 2024; e.g., OCO-2/3, Lin et al., 2023; Li, 2024; Nelson et al., 2024) to estimate emissions from point sources and urban regions are gaining traction as reliable and necessary tools for Measurement, Monitoring, Reporting, and Verification (MMRV) (CEOS-CGMS Joint Working Group on Climate Greenhouse Gas Task Team, 2024). However, because methods relying on Global GHG Mappers to estimate spatially distributed fluxes often cannot currently provide precise information, they are not part of the ongoing effort for MMRV and related actions, and as such, there is limited incentive to support top-down methods on scales that would enable their use for this purpose.

For the trace gas observation and modeling community to provide actionable information for climate mitigation, emissions verification, and the design of management strategies, we must be able to provide trace gas flux estimates for point source and diffuse emissions at local to regional scales (1–500 km). Part of the challenge is the current generation of models are not well equipped to ingest all available information. As a community, we need to identify use cases and corresponding scales where top-down methods are most effective and complementary to inventories. Then, we can develop a modeling framework that can leverage the full quantity and diversity of available data to support action at scale and with high accuracy and precision.

Here we will define the inverse problem, its challenges, and opportunities to address these challenges at different scales (Chapter 3). A new generation of models and space-based GHG and wind remote sensing tools show promise for observing and simulating the small to regional scales at which vertical and horizontal mixing occur, with near-global coverage. We will outline the current and future state of wind (Chapter 4) and GHG (Chapter 5) observations, providing insights into current capabilities and limitations for tracking atmospheric transport, and deliver improved sectoral attribution of carbon emissions and removals. Chapter 5 will summarize global modeling capabilities and priorities for improving the statistics of vertical mixing at regional scales. We synthesize findings in Chapter 7 and discuss how the combination of wind and GHG observations with high-resolution models will strengthen our knowledge of both.

3. SCALE DRIVES APPROACH

Trace gas modelers work at different scales to attribute carbon exchange to processes relevant to policy and MMRV, as well as to quantify natural exchanges of GHGs. The measurement needs for both trace gas and winds are a function of the trace gas flux that must

be quantified, as well as the dominant atmospheric transport processes. We define three key scales, both in terms of spatial extent (i.e., the size of the domain in which fluxes are estimated) and resolution (the scale at which fluxes are being estimated within the domain), in the context of trace gas emission and transport processes that are observable from satellites, and that are important to different communities of trace gas modelers, but currently have unmet needs in the Program of Record (see Figure 3.1):

(1) **Local Scale:** 1–10 km spatial extent, representing primarily anthropogenic processes dominated by point source (e.g., power plants, livestock facility) or fugitive (e.g., landfill leak) emissions or removals (e.g., carbon capture). Local scale requires carbon flux resolutions of 10–100 m to capture point emissions and removals. These scales are influenced by boundary layer turbulent transport nested within large-scale atmospheric flows. Deep convective mixing (i.e., caused by clouds and weather systems) does not need to be quantified.

(2) **Small Region Scale:** 10–500 km spatial extent, representing anthropogenic (e.g., transportation), managed (e.g., agricultural) and natural (e.g., forests) processes across cities, states, and small countries, comprised of spatially distributed and diffuse carbon sources and sinks. The small region scale requires carbon flux resolutions of 1–100 km to capture multiple spatially distributed area fluxes. The regional scales are influenced by both boundary layer turbulence and mesoscale (2–200 km) motions. Often deep convective mixing (i.e., caused by clouds and weather systems) does not need to be quantified.

(3) **Large Region Scale:** > 500 km spatial extent, representing mixed natural and anthropogenic processes over larger regions with similar political, vegetation, and climatic influence, and driven by diffuse carbon sources and sinks. The large region scale requires carbon flux resolutions of 100–500 km to capture multiple dominant large area fluxes. Winds at these scales are primarily driven by synoptic (~1000 km) dynamics, associated with large weather systems (e.g., extratropical cyclones and jets). Deep convective mixing (i.e., clouds, weather systems) must be quantified accurately.

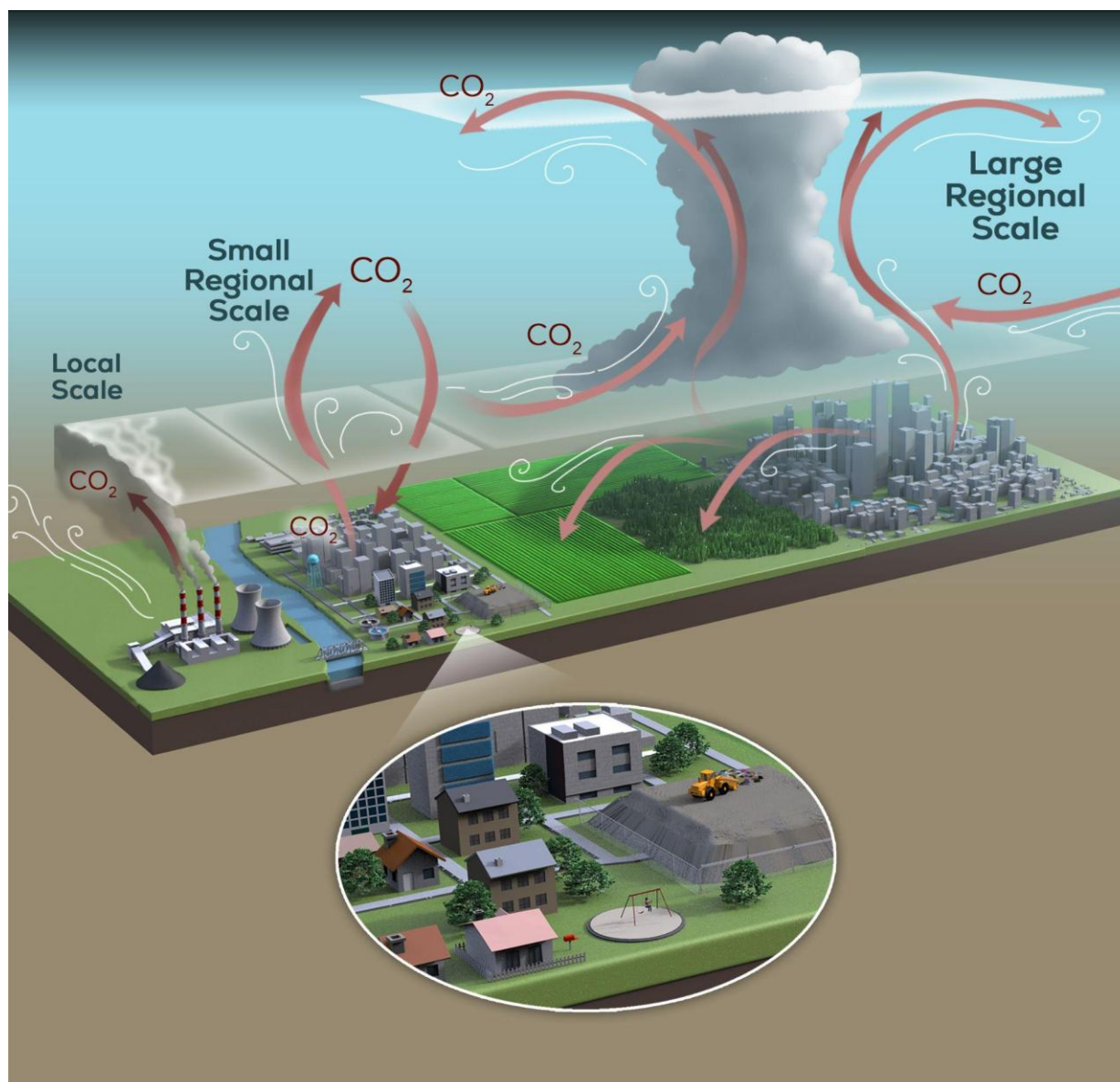


Figure 3.1. Scale requirements for GHG flux estimation. There are three primary scales with unmet GHG needs based on current and planning GHG observing systems: Local Scale (*left*), Small Region Scale (*middle*), and Large Region Scale (*right*). The local scale represents a system dominated by a single surface location (e.g., oil facility, afforestation project, CO₂ removal technology) and localized transport (boundary layer turbulence) process. The small regional scale represents a system consisting of multiple surface-based sources or sinks and transport processes, largely confined to the atmospheric boundary layer. The large regional scale consists of multiple natural and anthropogenic surface sources and sinks and horizontal and vertical mixing processes that encompass the entire troposphere.

Credit: Keck Institute for Space Studies/Victor Leshyk

3.1 LOCAL SCALE

The local scale is defined by trace gas sources originating from a single, specific location, typically at the scale of individual (< 1 km) or multiple (< 10 km) industrial facilities (e.g., power

plants, cement factories, landfill) (see “Local Scale” in Figure 3.1). This can include point source emissions from fossil fuel factories, fugitive emissions from landfills and oil and gas facilities, or negative emissions by CO₂ removal (CDR; e.g., Carbon, Capture, Utilization and Storage, or CCUS). In meteorological terms, the local scale refers to a blend of microscale and local scale in which atmospheric mixing is confined primarily to layers near the surface and/or within the atmospheric boundary layer (ABL). In trace gas modeling terms, the local or “plume” scale accounts for the direct effect of point source emissions or removals within an unmixed or poorly mixed volume of air. The plume scale is relevant for detecting point source emissions or removals of air pollutants, particulate matter, and GHG emissions. This scale is well observed for both GHGs and winds only in select locations and for limited applications.

Use Case Example: Detecting and Mitigating Fugitive Emissions

The rate of growth in global CO₂ 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. While this represents progress, emissions of both CO₂ and methane (CH₄) continue to rise. CO₂ removal projects can help slow the growth of GHGs, but until these projects are implemented at scale, decarbonization and leak mitigation remain a necessary path to support net zero emissions goals. Recent work has shown that mitigation of CH₄ super-emitters (such as landfills and oil and gas facilities), which make up a sizable contribution to total emissions over large basins, can have significant benefits through specific isolation and remediation of relatively few sources (Cusworth et al., 2022). High spatial resolution airborne and spaceborne instruments have been extremely valuable for detecting, quantifying, and mitigating emissions and leaks from single and multiple point sources (Cusworth et al., 2022; Nelson et al., 2024; Thorpe et al., 2023).

Opportunities and Challenges

Classic atmospheric measurement techniques include eddy covariance (for area fluxes, 1–2 km²) and spaceborne facility-scale plume monitors (for point sources, < 1 km²). These atmospheric measurements rely on the mixing of gases into the atmosphere via atmospheric turbulence, and are effective while the plumes are still being mixed into the ABL. Plume dispersion from point source emissions is currently well observed from space for large sources of CH₄ and CO₂ from active facility-scale plume monitors such as GHGSat, Earth Surface Mineral Dust Source Investigation (EMIT), and CarbonMapper (e.g., Cusworth et al., 2022). These instruments are highly sensitive to facility scale point sources but observe a very small fraction of the Earth’s surface. MethaneSat, which lost contact with mission operations in June 2025, offered a wider swath (200 km) for improved mapping of global oil and gas fields. While facility-scale plume monitors are improving detection of local CH₄ plumes, the ability to precisely detect CO₂ plumes from less intense, or more diffuse, leaks, emissions, and removals, for

example from landfills or direct air capture, represent an important measurement challenge moving forward.

Flux estimation approaches, including Gaussian plume models, large eddy simulation (LES), and integrated mass enhancement (IME), are facilitated by the relatively high contrast in concentration inside the plume compared to ambient conditions. Accurate measurements of wind speed and direction are needed to both identify the plume characteristics and estimate the emission size. Measurements of surface buoyancy, atmospheric static stability and wind shear are necessary to characterize the details of turbulent vertical and horizontal transport. Coarser resolution wind products combined with Lagrangian modeling methods might be sufficient for a similarly coarse source estimation. Gridded observation-constrained model winds (e.g., from NOAA's High-Resolution Rapid Refresh, HRRR) with grid spacings of 3 km horizontally can be corrected to capture smaller scales using observed/modeled plume shape. More challenging cases include emissions or removals with smaller magnitudes or that occur in the presence of relatively large biogenic fluxes. In each case, discriminating emissions from their background becomes critical. An additional challenge lies in quantifying plume altitude and emission injection height, which can vary significantly due to the high dependence on meteorological conditions (particularly temperature and wind). Together, with the vertical gradient in horizontal wind speed, uncertainty in injection height induces uncertainty in the point source emissions contributing to the plume.

3.2 SMALL REGION SCALE: 10-500 KM EXTENT, 1-100 KM RESOLUTION

The small region scale is defined by multiple point and diffuse GHG emissions. Regional domains of 10–500 km often encompass heterogeneous landscapes and multiple trace gas source or sink processes (see “Small Regional Scale” in Figure 3.1). Common examples of areas of interest include oil and gas basins, urban areas with a mix of fossil fuel emissions and biospheric exchange, agricultural areas, and countries comprising multiple natural, managed and anthropogenic sectors. The goal of constraining processes at small region scale is to ensure that, when extrapolated over areas and sectors of interest, all processes, emissions, and removals are accounted for, and bottom-up models and inventories are accurate.

In meteorological terms, small regions are driven by a mix of microscale and mesoscale circulations, including mixing within the ABL, entrainment of free tropospheric air into the ABL, free troposphere (FT), and horizontal advection. Transport at these scales, either within the ABL or through exchange with the FT, often leads to mixing of surface sources and sinks from multiple processes, making the attribution of carbon fluxes to a particular sector (e.g., vehicle emissions vs. biospheric uptake) particularly challenging. Equally important for flux estimation are the concentrations of the gas surrounding the small region area; inversion methods used to calculate surface exchange require knowledge of enhancement relative to the estimated

background concentration. These scales represent a critical link between small-scale processes, which are difficult to observe from space, and global-scale models, which can be computationally expensive to implement with high resolution. This scale is currently partially observed with respect to GHG and winds.

3.2.1 Use Case Example 1: Tracking Fossil Fuel Emissions in Urban Regions

On the order of 70% of global fossil fuel emissions originates in cities (Gately & Hutyra, 2017). An important challenge in global decarbonization efforts is determining whether cities and countries are on track to reduce emissions (e.g., 10% per year) and meet their climate targets. This requires disentangling and tracking progress across different emission sectors (e.g., energy, transportation, municipal) and identifying priorities for further emissions reductions. In general, fossil emissions have declined across the group of developed countries of the Organisation 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 fossil fuel CO₂ increase in recent years (Friedlingstein et al., 2025). The ability to leverage top-down and bottom-up information to inform progress across different emissions sectors requires disaggregation of urban emissions to finer temporal and spatial scales.

Because of the many assumptions required to disaggregate emissions, sub-urban and sub-annual emissions are generally more uncertain compared to urban scale estimates as emissions become decorrelated from activity levels (Hogue et al., 2016; Oda et al., 2019, 2021, 2023). Recent work leveraging tower, network, and spaceborne observations shows increased fidelity for estimating urban scale emission rates (Basu et al., 2020; e.g., Duren & Miller, 2012; Kiel et al., 2021; Lauvaux et al., 2020; Meijer et al., 2023). This fidelity is sensitive to the spatial and temporal resolution in observational data. For example, McDonald et al. (2014) showed that the CO₂ flux inversion for Los Angeles at 10 km does not show any spatial structure in the fluxes (e.g., freeways and city are mixed in the grid), while the same inversion at 1 km starts resolving the freeways from the background and at 500 m also resolves the arterial roads along with the freeway. This type of sectoral-level attribution (i.e., distinguishing emissions between the transportation and energy sectors) is key for identifying, understanding, and prioritizing mitigation efforts. Existing and future monitoring efforts have significant potential to reduce carbon budget uncertainties and to directly inform GHG mitigation and tracking efforts. Key remaining challenges involve (a) sectoral-level attribution, and (b) long-term trend detection and quantification across sectors.

3.2.2 Use Case Example 2: Nature-based Climate Solutions

Nature-based climate solutions (NbCS) are actions that seek to protect, sustainably manage, and restore natural and modified ecosystems for the benefit of people and nature. Such actions are essential to help mitigate the impacts of climate change and reduce global

temperatures. Forest-focused, nature-based solutions (F-NBS), such as forest management through afforestation and reforestation, are particularly important. They removed an estimated 0.5 GtC yr^{-1} from 2014 to 2023, representing the vast majority of all nature and technology-based CO_2 removal (Vaughan et al., 2024). The high readiness level and high GHG mitigation potential offered by NbCS has led to ambitious restoration commitments, with F-NBS forming an integral part of many countries' net-zero commitments and Nationally Determined Contributions (NDCs) to the United Nations Framework Convention on Climate Change (UNFCCC) (Gidden et al., 2023). The voluntary carbon market is a key mechanism to channel carbon finance into forest restoration activities, and monitoring carbon impacts. The motivation for this is to generate carbon credits, each equivalent to 1 metric ton of CO_2 , which are sold as carbon offsets. With carbon credits from forest conservation and restoration projects being used to offset emissions elsewhere, it is essential they are quantified and regulated using robust monitoring methods and are linked to real emission avoidance or removals to avoid over-crediting. In theory, top-down GHG flux estimation based on atmospheric observations and atmospheric modeling could offer additional valuable insight, but its current limited ability to detect project-scale emission reduction or removal may restrict its application in mitigation monitoring.

Opportunities and Challenges

The gap between global-scale carbon monitoring and local action hinders GHG mitigation efforts and the ability of cities, states, and countries to assess progress toward meeting emissions goals and climate targets. Currently, spaceborne observations provide regional coverage but struggle to capture small-scale phenomena, while ground-based observations can capture these details but implementing extensive monitoring networks globally is impractical. Therefore, finding a balance between remote sensing and in-situ observation capabilities is key to addressing the challenges of carbon flux estimation at regional scales. For small-region source areas, where the time of atmospheric transport across the region is on the order of a day or less, accurate flux retrievals can often be obtained solely with measurements within the ABL. Dense measurements, along with high spatial resolution, are necessary to accurately estimate the spatial structure of emissions and removals. In these situations, knowledge of the frequency of venting episodes from surface fluxes—along with ABL height and wind speed and direction—is key, especially in areas with complex terrain and background influence. An alternative to direct wind measurements is the use of trace gas data to infer wind patterns within and above the ABL. This may aid in the quality of reanalysis products used in top-down inversions through DA and/or validation and refinement of vertical mixing processes.

We are now in a new era of high-resolution global modeling, with kilometer-scale (1–10 km) and hectometer-scale (0.1–1 km) modeling now computationally feasible. Kilometer-scale

models bring key advantages for estimating GHG transport, as the smaller-scale wind flows come into sharper focus, though the smaller grid spacing introduces challenges in that we do not currently have observations to constrain the details of the fine-scale temperature, moisture, and wind gradients. While hectometer-scale models resolve deep convection and permit shallow convection, they cannot resolve at subgrid (turbulent) scales that are critical to ABL-FT exchange (Guichard & Couvreux, 2017). In addition, while hectometer-scale models resolve fine-scale weather, they may place individual systems (e.g., convective storms) in the wrong place and/or at the wrong time. Even with these limitations, the flows they resolve improve statistics on regional scales, and hence the trace gas budget at regional scales too.

3.3 LARGE REGION SCALE: > 500 KM EXTENT, 100-500 KM RESOLUTION

Applications at large region scales span domain sizes of individual biomes up to entire continents, e.g., diffuse fluxes over agricultural and natural ecosystems and, in some instances, large urban landscapes (see “Large Regional Scale” in Figure 3.1). Large-scale fluxes over land and ocean inform our understanding of the global carbon cycle and its mean response over time to changes in anthropogenic forcing. Large-scale fluxes are diffuse relative to urban or point source emissions, but still important to quantify for continental to global scale carbon budget closure. At this scale, atmospheric transport of trace gases is not limited to the ABL. Exchange of air between the ABL and the FT, driven by synoptic and mesoscale weather events, lead to deeper mixing of surface fluxes, and in addition to ABL depth and winds, frontal lifting, lifting due to convergent flows, and cloud convective mixing must all be considered. Estimates of ABL height, and trace gas vertical gradients are useful tools at this scale, especially when combined with in-situ measurements that exist in regional networks. This scale is currently partially observed with respect to GHG and winds. While there are no current missions that directly address ABL height or vertical gradients, ABL dynamics and regional scale fluxes are priorities according to a midterm assessment of progress toward implementation of the 2018 NASA Earth Science Decadal Survey (Committee on the Review of Progress Toward Implementing the Decadal Survey-Thriving on Our Changing Planet: A Decadal Strategy for Earth Observation from Space et al., 2024)

Use Case Example: From Emissions to Extremes and Early Warning Signals

New synthesis observational-modeling efforts should be aimed towards reducing uncertainties in the characterization of the global carbon budget by accounting for changing anthropogenic emissions, as well as changes in the natural sources and sinks and the carbon-climate feedbacks under continuing climate change. Several studies indicate uncertainties may be concentrated in highly meteorologically active areas, i.e., along storm tracks. On large scales, the main uncertainties in the current budgets stem from land-use practices, the terrestrial northern extra-tropics, as well as the ocean sink (Friedlingstein et al., 2025). In the future, the

role of extremes, compound extremes (e.g., combination of extreme events), and cascade (series of extreme events) is likely to play a more important role (Schimel & Carroll, 2024) and might lead to regional or global tipping points (Romanou et al., 2025). We must meaningfully extract trends and variability at seasonal, interannual, and decadal scales, but also identify the impact of climate extremes on the regional and global carbon cycles in terms of magnitude, reversibility and resilience and possibly identify early warning signals of likely tipping points.

Opportunities and Challenges

Reducing the uncertainties in the GHG transport terms, via advective, turbulent, and convective processes as they are estimated from gridded analysis products is critical. The Earth system has many interfaces that attenuate trace gas flows that remain poorly observed, e.g.,: the air-land-ocean-ice interfaces; interactions over different types of vegetation, soil, or urban/rural systems; and the interaction between the ABL and the FT. New measurements targeting critical processes require improved spatial and temporal sampling, increased precision, and improved traceability to emission and removal processes. In addition to new observations, we need better data-assimilative models, and prediction systems (coupled and Earth system models, or ESMs) that are more skillful over a broad range of scales and capture the growing role of climate extremes.

4. CURRENT AND FUTURE STATE OF WIND OBSERVATIONS

Measurements of winds in the Earth's atmosphere are made routinely from a variety of platforms, which can be divided into two broad categories: in-situ and remote sensing. Each type of measurement has its own set of strengths and limitations. In-situ observations are made at or near the Earth's surface over land and ocean, as well as from airborne platforms including balloons (radiosondes) and aircraft (primarily via sensors located on commercial flights). In-situ measurements provide direct estimates of wind but are point observations and their representativeness of larger regions is limited. In addition, in-situ ground and balloon observations are limited to land, and radiosondes are typically only launched twice per day. While wind measurements are collected at the ocean surface from buoy measurements, these are sparse, and primarily available near the coasts. Aircraft in-situ wind observations are limited to flight lanes and are concentrated most strongly around airports.

Remote-sensing measurements are made from ground via Doppler radar and wind profilers, and from space via a variety of satellite measurements. Broadly speaking, remote sensing methods record the amount of energy reaching a sensor following emission from an artificial or natural energy source, transfer through the atmosphere, and absorption or re-

emission in the atmosphere. The three primary emission sources include radars/lasers (active), the Sun (passive shortwave), and the atmosphere (passive thermal). Active and passive shortwave techniques measure energy reflected from clouds and aerosols, while passive thermal techniques measure the re-emission of absorbed light by the atmosphere as longwave radiation. Passive remote sensing measurements have the advantage of much larger spatial coverage (global, in the case of satellite observations) but are limited by the fact that they require image processing techniques to convert sequences of spatial fields (e.g., horizontal images of clouds or trace gases) into estimates of wind. Active measurements rely primarily on the Doppler shift in radiation reflected from aerosols, clouds, and hydrometeors. This provides a more direct estimate of wind speed, but only along the direction of sight of the radar or lidar, and typically over a very limited horizontal region.

A comprehensive list of current and near future wind measurements can be found in Table 4.1. The primary spaceborne measurement techniques are illustrated in Figure 4.1. When examining the needs of wind information for GHG applications specifically, and for transport of pollutants and aerosols more generally, there are some key considerations:

- 1) Spatial and temporal coverage,
- 2) directionality—whether vertical, horizontal, or line-of-sight—and
- 3) uncertainty, including both random error and bias.

Each consideration has critical implications for the transport of gases, and a review of the current capabilities and gaps helps illuminate the needs for future wind measurements.

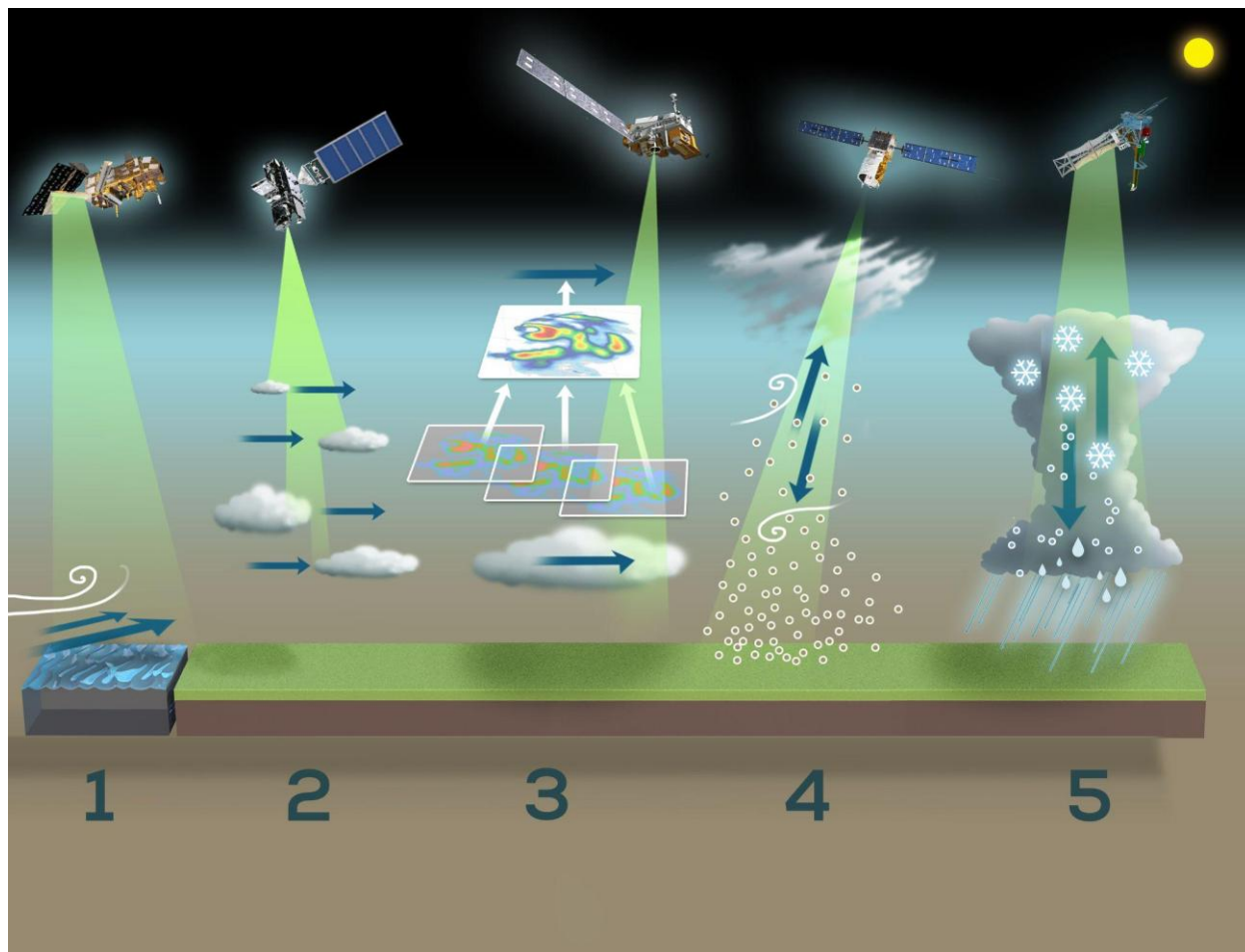


Figure 4.1. Depiction of spaceborne remote sensing techniques for wind. Five methods are illustrated, including (left to right) (1) scatterometer- and polarimeter-based measurements of wind-driven surface waves, (2) tracking the motion of clouds, (3) Doppler wind lidar (DWL) measurements of scattering by molecules, aerosols, and clouds, (4) radar reflectivity measurements of cloud vertical mass flux, and (5) tracking the motion of trace gases such as water vapor. Credit: Keck Institute for Space Studies/Victor Leshyk

4.1 SPATIAL AND TEMPORAL COVERAGE

4.1.1 In-Situ Wind Data

As noted above, the spatial coverage of in-situ measurements is limited to locations over land, ocean buoys, and along air routes. Measurement locations are typically limited to places in proximity to population centers. Lack of economic resources and/or political constraints on data sharing further limit data availability. The result is a concentration of in-situ data over land, over ocean near coasts, and in regions with high population and economic wealth. This is clearly depicted in Figure 4.2, which shows the distribution of land and ocean surface observations circa 2017, along with 24 hours of commercial aircraft observations from

Table 4.1. Summary of current and planned wind observation capabilities. A link to this review of wind observation capabilities can be found at <https://care-weather.notion.site/11a2b1716e9080529486f24007cf6ca3?v=7da66531d99b4f28b90f2cdd4d4183ce>. References cited in brackets in the Instrument column are listed in Appendix D of this report.

Comparison of Wind Measurement Instruments and Products.

Instrument	Description	Ct.	Type	Accuracy	Res. (u,v)	Refresh	Coverage	Date Range	Status
Doppler Shift									
ALADIN on Aeolus [1], [2]	Doppler LIDAR measuring laser reflections of atmospheric molecules and particles.	1	Speed	3 m/s	—	1 week	80° S to 85° N, 16–26 km Alt	2018–2023, 2030+	End of Life
				2 m/s	—		2–16 km Alt		
				1 m/s	—		0–2 km Alt		
Earthcare [3], [4]	Vertical winds obtained from a profiling Doppler radar.	1	Speed	1.3 m/s	0.5 km	2.5 weeks	-87° to 87°	2024+	Operational
Wivern [5], [6]	Dual-polarized conically-scanning Doppler radar measuring line-of-sight winds.	1	Speed	2 m/s	—	36 hours	Global	TBD	Funded
Object Tracking									
AIRS on Aqua [7]–[9]	Motion vectors from consecutive spectral IR polar water vapor soundings.	1	Speed	7 m/s	41 km	3.3 hours	Poleward of 70°	2002+	Operational
GOES [10], [11]	Feature tracking of time resolved visible/IR images (radiances) or retrievals (water vapor).	1	Speed	7.5 m/s	2 km	15 mins	Lat -80° to 80°, Lon 150° to 360°	1978+	Operational
IASI [9], [12]–[16]	Pair of infrared sounding interferometers flying one after the other in 50 min succession.	2	Speed	7 m/s	20 km	12 hours	Poleward of +/-50°	2018+	Operational
INCUS [17], [18]	Time-differenced profiling radar and radiometer measuring convective updrafts in tropical storms.	3	Speed	4.2 m/s	3.1 km	—	—	2026–2028	Funded
Sentinel-3 SLSTR [11], [19]	Thermal infrared radiometer.	2	Speed	3.64 m/s	5 km	22 hours	Lat -88° to 88°	2016+	Operational
Surface Stress									
ASCAT on MetOP [20]–[26]	Active scatterometers (radars) observing the ocean surface from multiple look angles.	2	Speed Direction	2 m/s 20°	6 km	18 hours	10-m above ocean, global	1991+	Operational
CYGNSS [27]–[30]	GNSS receiver measuring specular reflection of GNSS signals reflected off of Earth's surface.	1	Speed	2 m/s	25 km	—	38° S to 38° N	2016+	Operational
Sentinel-1 SAR [31], [32]	Active radar observing fine resolution wind speed and inferring direction from streaks in the waves.	1	Speed	1.6 m/s	1 km	6 days	10-m above ocean, global	2014+	Operational
Sentinel-3 SRAL [33]–[36]	SAR altimeter measuring ocean wind speed at nadir.	2	Speed	1.5 m/s	3 km	2 weeks	10-m above ocean, global	2016+	Operational
SSM/I (DMSP) [37]–[39]	Microwave radiometer observing wind speed over the ocean surface.	19	Speed	2 m/s	25 km	18 hours	-88° to 88°	1987+	Operational
Veery [40]	Constellation of active small-satellite scatterometers observing the ocean surface from multiple look angles.	12–36	Speed Direction	1.6 m/s 11°	6 km	1 hour	10-m above ocean, global	Available in 2026	Funded
WindSat [41]	Polarimetric microwave radiometer observing the ocean surface with a variety of frequencies and polarizations.	1	Speed Direction	2 m/s 2°	25 km	36 hours	10-m above ocean, global	2003–2020	End of Life
WSF-M [42]–[44]	Polarimetric microwave radiometer observing the ocean surface with a variety of frequencies and polarizations.	2	Speed Direction	2 m/s 30°	25 km	2 days	10-m above ocean, global	2024+	Commissioning

October 2022. Note that surface observations are only representative of conditions within the lowest few tens of meters in stable (e.g., nighttime) conditions and up to ~1 km in well-mixed (e.g., daytime) conditions. In-situ observations of winds > 1 km above the surface are extremely sparse.

4.1.2 Remotely Sensed Wind Data From Satellites

Wind can be measured remotely using three fundamental methods: Doppler shift measurement, feature tracking, and measurement of stress at a fluid interface. These methods are summarized in Figure 4.1. The Doppler shift (e.g., Methods 3 and 4 in Figure 4.1) is measured using active sensors (radars and lidars) that measure the frequency shift of transmitted signals reflected from moving particles in the air. Many remote sensing systems can track motion (e.g., Methods 2 and 5 in Figure 4.1) by observing a body of air at multiple points in time, then using feature identification and tracking techniques to provide a motion vector between the two points. Finally, at the air-sea interface, wind stress deforms the ocean surface (e.g., Method 1 in Figure 4.1), changing the profile of directions to which the signals transmitted by active sensors are scattered off the surface and the profile of polarizations in which thermal radiation is emitted from the surface.

Satellite observations generally provide increased sampling in time and space at a global scale relative to in-situ observations. The most widely available satellite observations over lower and middle latitudes come from geostationary (GEO) platforms, which provide data at several different wavelengths in the visible and infrared wavelengths at a cadence of approximately every 10–30 minutes and on spatial grids of pixels 2–10 km on a side. At latitudes greater than 45 degrees, distortion of the images due to Earth’s curvature is increasingly problematic, and the data are generally not deemed to be useful at latitudes greater than 60 degrees. In contrast, low Earth-orbiting (LEO) satellites sample intermittently (a few times each day) at low to middle latitudes (< 45 degrees) and more frequently in high-latitude polar regions and are not susceptible to latitude-based image deformation, providing a natural complement to geostationary data.

Nearly all wind information from GEO and LEO instruments is derived from the translation of features observed in sequences of images. By comparing two or more images, and identifying spatial patterns in each image, the translation of features can be converted to wind velocity vectors. These feature-tracking winds are commonly referred to as atmospheric motion vectors (AMVs) and are derived by tracking cloud features and also estimates of trace

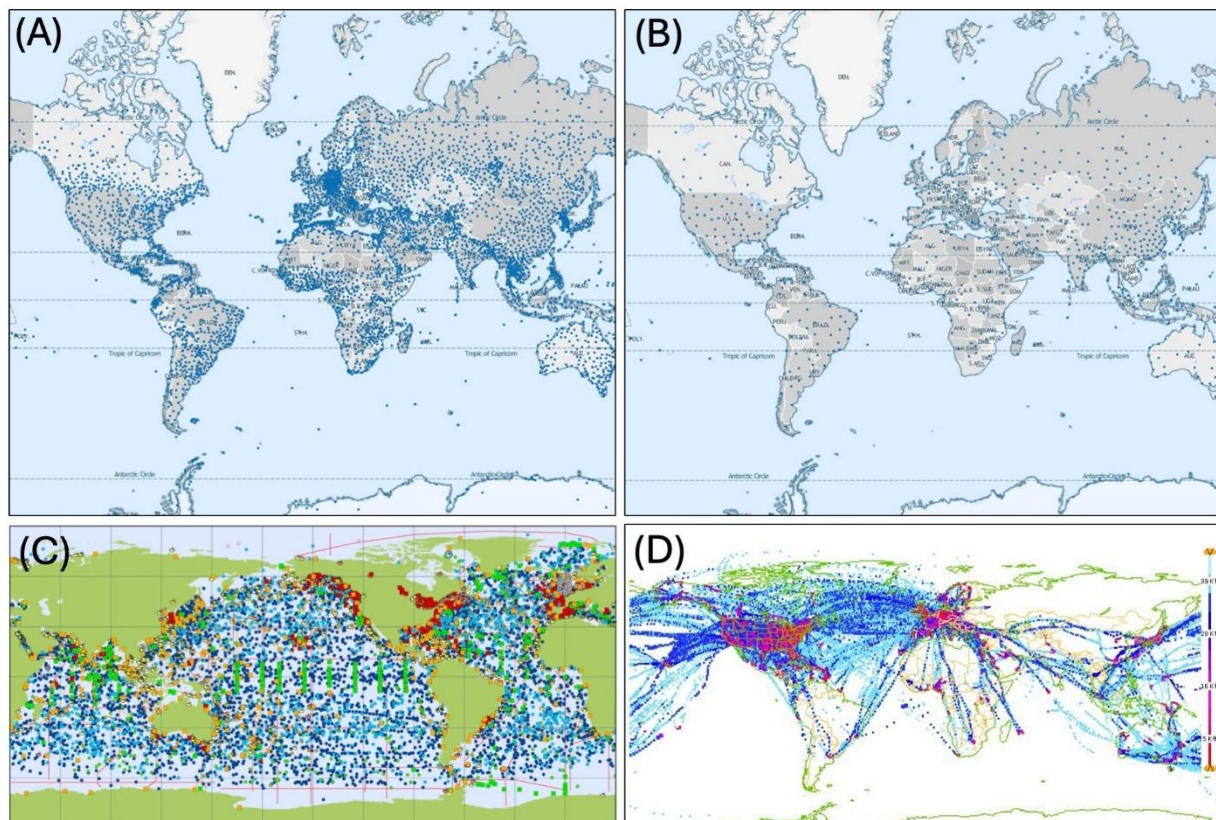


Figure 4.2. Depiction of the global distribution of (A) surface in-situ observations over land, (B) radiosonde observations, and (C) surface and profile observations over ocean from profiling floats, data buoys, ship based measurements, moorings, and tide gauges (from Lindstrom, 2018). Observation locations are valid as of 2017. (D) Distribution of 24 hours of observations from commercial aircraft from 31 October 2022. Credit: WMO and Lindstrom (2018).

gas (e.g., water vapor) concentrations. All current and planned GEO missions, and the majority of LEO missions, rely on passive measurements of radiation from the Earth's surface and atmosphere, for which feature tracking is the only option for wind retrieval. There are well-known sources of systematic error in AMVs, which we discuss in more detail in Section 4.2.

Several LEO instruments observe wind actively, via measurement of the Doppler shift in frequency.

Doppler winds are only available along the line of sight of the sensor, meaning that, in most cases, they provide only a single component of the 3D wind. Doppler wind lidar (DWL) transmits and receives in UV, visible, and near-infrared wavelengths and has been shown to be successful from aircraft for decades. Recently, the European Space Agency (ESA) operated the first spaceborne Doppler wind lidar on the Aeolus mission (2018–2023). Lidar provides vertical high-resolution information, but only along a narrow track. In addition, because optical wavelengths are rapidly attenuated in clouds, DWL wind estimates are only available in cloud-free regions. Due to the expense of spaceborne lidar, very few instruments operate at a time,

and, in fact, until the European Organisation for the Exploitation of Meteorological Satellites (EUMETSAT) launches an Aeolus follow-on in the 2030s, there are no planned spaceborne DWL observations.

ESA recently launched the first-ever spaceborne Doppler radar mission EarthCARE (Earth Cloud, Aerosol, and Radiation Explorer), which measures only the vertical component of wind, and only inside of clouds. Early results appear promising, but it should be noted the relatively high frequency of the EarthCARE radar (94 GHz) limits its observations to those regions that do not contain heavy rainfall. Two other Doppler radar concepts are currently in development: the Atmosphere Observing System (AOS) storm platform, which would feature a low-frequency (13.6 GHz) Doppler radar aimed at vertical motions within precipitating regions; and the WInd VElocity Radar Nephoscope (WIVERN) concept from ESA, which features a 94 GHz scanning Doppler radar providing information on both horizontal and vertical winds inside of clouds. In addition to Doppler shift, motions can be obtained from active radar sensors via time differences in the reflected signal. The forthcoming Investigation of Convective Updrafts (INCUS) mission, launching no earlier than September 2026, will provide estimates of vertical mass flux from a triplet of spaceborne radar-reflectivity observations spaced 30, 90, and 120 seconds apart.

Current and near-future satellite wind observations can be summarized as follows:

- 1) The vast majority of wind observations are of horizontal wind components;
- 2) the vast majority of vertical transport occurs within clouds; and
- 3) in-cloud vertical motion estimates require active spaceborne measurements that are necessarily limited in space and time.

It is unlikely a sufficient number of active spaceborne instruments will be launched in the next decade or longer. As such, the community will lack observations of vertical mixing in clouds globally or with regularity needed to constrain trace gas transport in atmospheric plume or inverse models. It is necessary, and more practical, to make better use of the limited active and passive horizontal and vertical wind data at our disposal. Data fusion and/or data assimilation (DA) approaches discussed in Sections 4.2 and 4.3, respectively, are a promising way to exploit multiple synergistic pieces of information from different remote sensing techniques (passive and active) and platforms (GEO and LEO).

4.2 WIND MEASUREMENT UNCERTAINTIES

The utility of any measurement is at least in part a function of its error, with sources and magnitudes of error depending on the measurement type. Sensors used in in-situ measurements are calibrated before deployment so that their error versus a reference is low; however, as sensors age, they may become biased. In addition, any in-situ measurement is only

sensitive to the immediate air it is exposed to. If, for example, there is significant spatial variability in the true wind field, then an in-situ wind measurement may not be representative of more than a very small region. If the aim is to characterize the properties of the flow field over a broader region than the immediate sphere of sensitivity of the in-situ measurement, then there will be an error of representativeness in the in-situ measurement. Such errors are challenging to quantify, as they depend on the state of the atmosphere.

Uncertainties in spaceborne wind estimates are even more complicated. Representativeness error is a factor, and, as with in-situ data, may be due to a satellite pixel size that is much smaller than the feature of interest. However, much more often the converse is true: the satellite pixel size is larger than the desired resolution of the field of interest. In addition to representativeness error, there may be errors in the conversion from the satellite measurement (e.g., voltage on a sensor) and the quantity of interest. For example, obtaining feature-tracking winds from the movement of clouds relies on: (1) sufficient texture in the cloud image, and (2) accurate assessment of the height of the cloud top (so that the wind may be assigned to the proper vertical location). In the case of tracking trace gas features, there are additional uncertainties associated with possible errors in the trace gas estimates themselves. Posselt et al. (2019) conducted a synthetic data experiment, converting water vapor from a numerical weather model into wind vectors by applying a feature tracking method. The authors quantified the uncertainty in the resulting AMVs by comparing the wind estimates to the “true” wind from the model. They found the uncertainties in the wind estimates were state-dependent, with errors that increase as a function of decreasing water vapor content and water vapor spatial gradient (Figure 4.3). They also found the errors peaked when the wind flow was oriented parallel to lines of constant water vapor content. In this case, there may be no apparent movement of the water vapor distribution while there is non-zero wind.

Uncertainties in active Doppler wind measurements are often more straightforward than those for AMVs. This is because the Doppler shift is directly related to wind magnitude and is a function of the signal-to-noise ratio of the observation. In the case of DWL, Doppler information from a range of sequential laser pulses can be averaged adaptively to optimize sensing properties. For example, in a relatively low signal-to-noise region (e.g., low aerosol content), one can choose to either retain high resolution and large noise, or to average a larger number of pulses to obtain lower uncertainty at the expense of spatial resolution. Because DWL

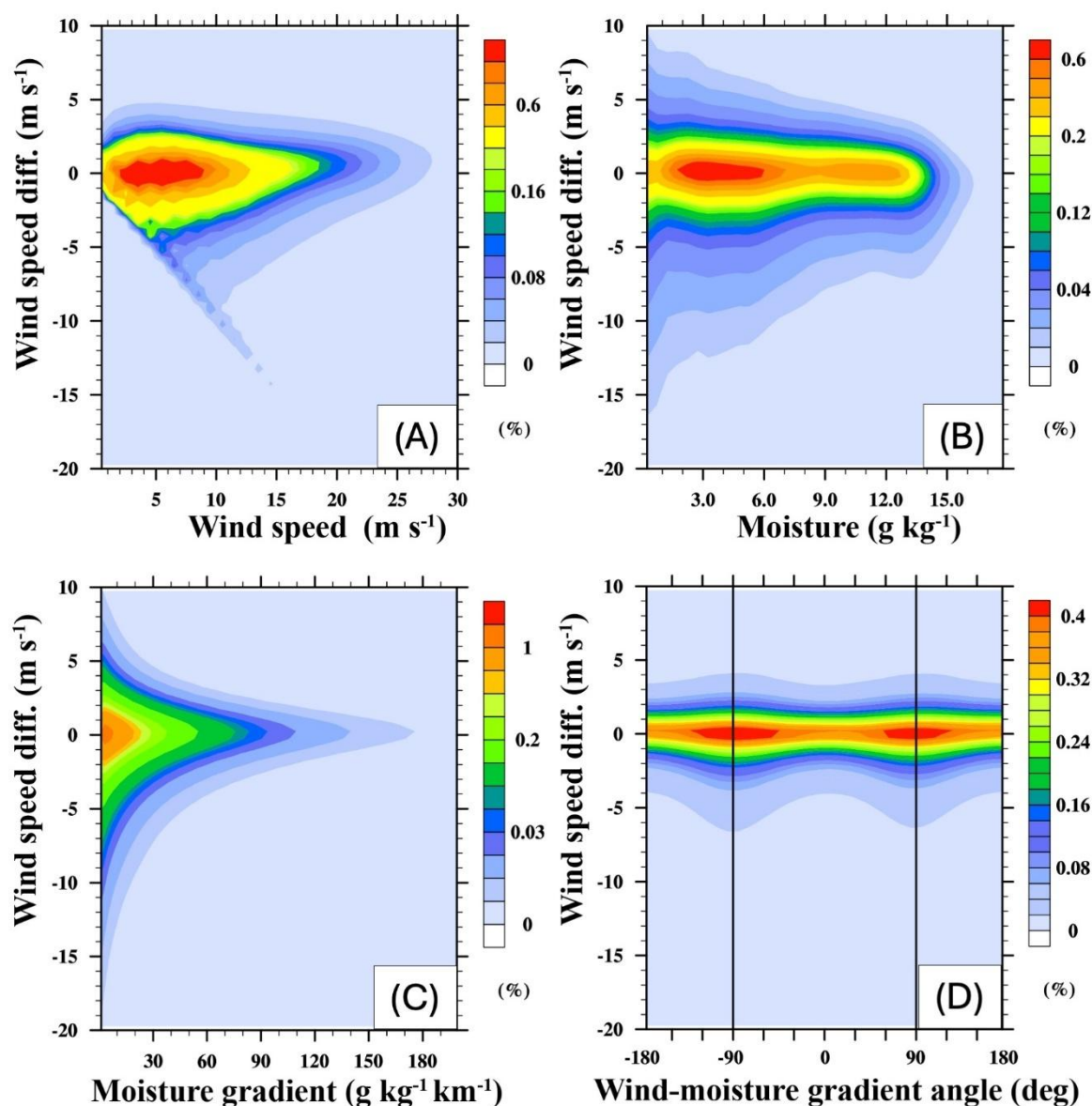


Figure 4.3. Difference between wind estimates from feature tracking and the “true” (modeled) wind (tracked - true) at the 850-hPa pressure level as a function of (A) water vapor content, (B) wind speed, (C) water vapor gradient, and (D) the angle between the wind direction and the water vapor gradient. Color shading represents the percentage of the total number of grid points that have a particular value of wind speed difference. Black vertical lines in (D) indicate the position of the $\pm 90^\circ$ -degree angles. Adapted from Figure 6 of Posselt et al. (2019). © American Meteorological Society. Used with permission.

is a more direct measurement of wind, it has high value as an anchor measurement, even though its coverage is low.

Errors in measurements can be mitigated by exploiting synergy among diverse measurement sources and techniques. For example, uncertainties in DWL wind estimates derive from entirely different sources than errors in AMVs. It is, therefore, feasible to use the spatially and temporally limited DWL wind measurements to correct for uncertainties in AMVs. Nguyen et al., (2024) conducted a set of simulation experiments in which they estimated AMVs from time sequences of modeled water vapor fields, and simulated DWL observations from modeled aerosol and atmospheric pressure. Using three months of simulated observations, they trained a random forest model on the differences between DWL and AMVs where there were intersections. They then used this model to modify the AMVs, correcting for bias in the observations. The result was a nearly complete removal of the bias in the AMV wind estimates (Figure 4.4).

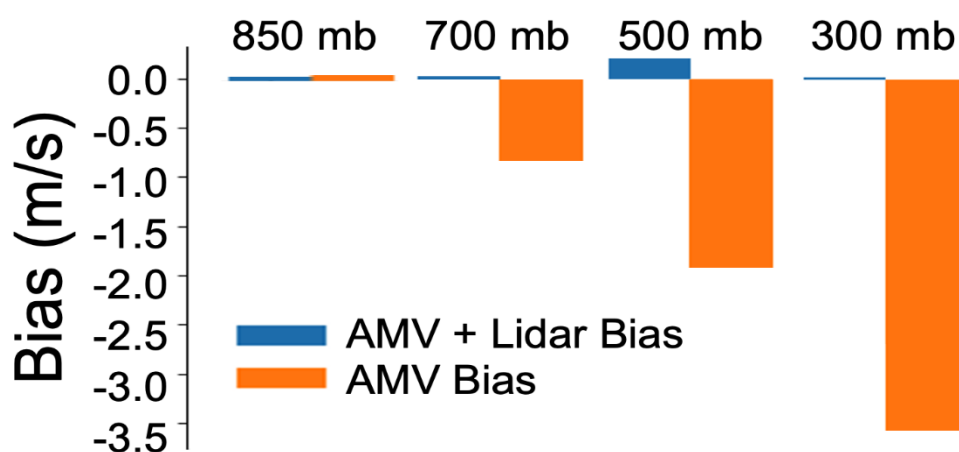


Figure 4.4. Bias in three months of AMV estimates at various vertical pressure levels before bias correction (*orange*) and after lidar-based bias correction (*blue*). Adapted from Figure 4 of Nguyen et al. (2024).

4.3 DATA ASSIMILATION

In-situ and spaceborne observations offer diverse, albeit incomplete, information on wind structure and dynamics at global scale across a range of environments. The ability to use this information to support GHG flux estimation needs represents an important but challenging opportunity, requiring improvements in wind coverage, retrieval, and uncertainty estimation.

Data assimilation (DA) could offer a more practical, short-term (next decade) route to improving GHG transport. Through DA, high-resolution space-based observations (see Table 4.1 and discussion above) of wind profiles and surface winds over land and ocean (via scatterometers) can provide strong constraints on modeled horizontal flows. Incorporating new observations, both ground-based and space-borne, into a DA system could provide a strong

constraint on wind flows down to scales of a few tens of kilometers and should improve forecasting and reanalysis of GHG budgets at the regional scale.

A successful DA framework already underway is the European Destination Earth (DestinE) flagship initiative² funded by the European Commission, involving ESA, EUMETSAT, the European Centre for Medium-Range Weather Forecasts (ECMWF), Copernicus, and others. DestinE aims to produce a digital twin of the Earth system at kilometer scales—essentially a highly accurate reanalysis product—to provide a single monitoring and modeling system to aid the development of mitigation measures and adaptation strategies. This involves improving modeling accuracy as well as developing higher-resolution DA that can make effective use of new higher-resolution space-based sensing and ground-based observational networks.

5. CURRENT AND FUTURE STATE OF GREENHOUSE GAS OBSERVATIONS

GHG observations, like their wind counterparts, can be divided into in-situ and remotely sensed measurements. CO₂, CH₄, carbon monoxide (CO) and other GHGs have unique absorption features across shortwave and thermal infrared spectral regions. Remotely sensed trace gas concentrations are made from surface, aircraft, and satellite-based instruments. In-situ observations are based on measurements of GHG concentration within a sample of air collected or observed from surface, tower, balloon, and airborne platforms. These point measurements can be made continuously in place and in real time in the field, using infrared gas analyzers, or in a lab, by collecting air in glass containers and analyzing the gases at a later time but with increased precision. A second class of in-situ methods relies on collocated measurements of wind and GHG fluctuations within a few meters to hundreds of meters above the surface to provide continuous estimates of land-atmosphere gas exchange over an area of land smaller (< 100 km²) than possible from in-situ and remote sensing concentration data, but limited in spatial extent (e.g., Pastorello et al., 2020).

A condensed summary of existing trace gas in-situ observations and remote sensing products is shown in Table 5.1 and Figure 5.1, respectively. We will focus here on CO₂ and CH₄. When determining how to best apply the extensive, ongoing trace gas observations, our considerations include (1) spatial and temporal resolution and revisit, and (2) uncertainty and bias in the measurement. Reviewing our current ability to detect trace gases and where these

² <https://destination-earth.eu/>

approaches have blind spots will indicate where future efforts can be directed for the biggest impact.

Table 5.1. Example of in-situ and remote sensing measurements of carbon and some non-carbon GHG flux and concentration datasets and methods.

Dataset	Methods	Citation
FLUXNET surface measurements Integrated Carbon Observation System (ICOS) The NOAA Global Greenhouse Gas Reference Network (GGGRN)	In-situ measurement of GHG flux and concentration: Eddy covariance towers, tall towers, surface flasks	Heiskanen et al. (2022); Pastorello et al. (2020); Schuldt et al. (2024)
The NOAA Global Greenhouse Gas Reference Network (GGGRN)	In-situ measurement of GHG concentration: Aircraft, balloon, AirCore	Karion et al. (2010); Schuldt et al. (2024)
Advanced Global Atmospheric Gases Experiment (AGAGE) flask network	In-situ measurement of chemically and radiatively important atmospheric gases	Prinn et al. (2018)
TCCON network Collaborative Carbon Column Observing (COCCON) network Network for the Detection of Atmospheric Composition Change (NDAAC)	Ground-based Remote sensing of GHG concentration: Lidar, Microwave Radiometers, Fourier-Transform Infra-Red (FTIR)	De Mazière et al. (2018); Frey et al. (2019); Laughner et al. (2024)

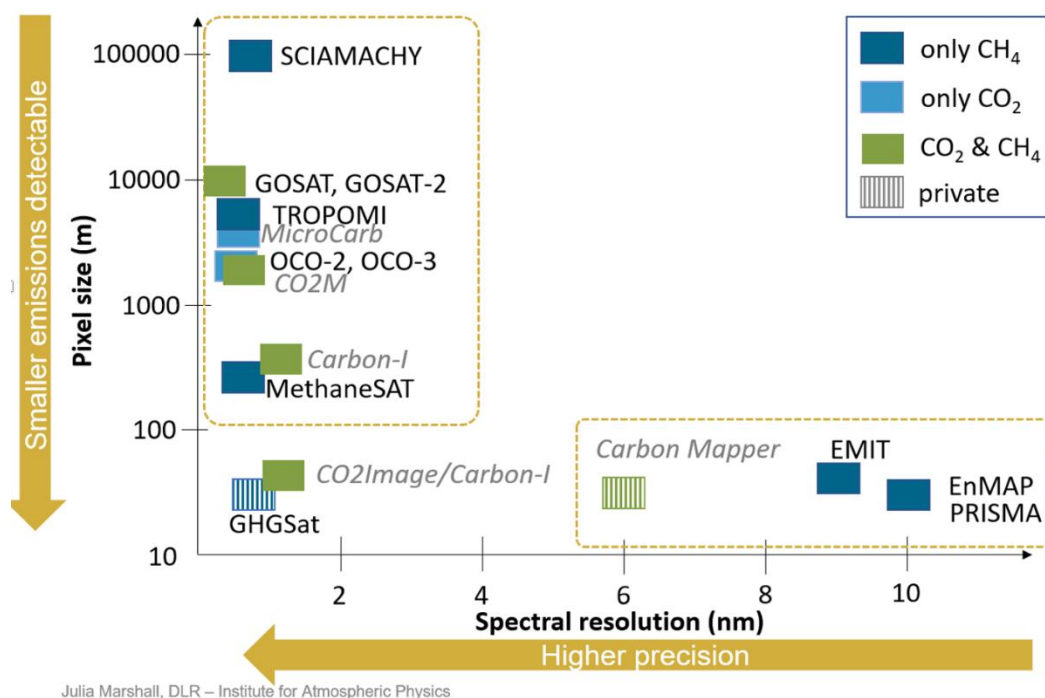


Figure 5.1. Summary of satellite-based remote sensing products comparing spectral resolution and pixel size. Gray text indicates the satellite is not yet launched.

Credit: Institute for Atmospheric Physics/Julia Marshall

5.1 SPATIAL AND TEMPORAL COVERAGE

Trace gases are trace because 99.96% of the atmosphere consists of nitrogen, oxygen, and argon, leaving a fractional amount (0.04%) to trace gases, including carbon-based GHGs (CO₂, CH₄, CO), non-carbon GHGs (H₂O, NO_x), aerosols, and pollutants that nevertheless have an outsized impact on air quality and climate. The requirements for space-based sensors to monitor trace gas variability and estimate surface flux depend on the species and class of emissions. This is illustrated by the diverse range of space-based sensors and trade space between spectral and spatial resolution (Figure 5.1).

Facility-scale plume monitors such as MethaneSat, GHGSat, CarbonMapper, NASA's Earth Surface Mineral Dust Source Investigation (EMIT), and the Italian Space Agency's PRecursoRe IperSpettrale della Missione Applicativa (PRISMA) are sensitive to GHG sources (most notably CH₄) at facility scale (~10–100 m) due to emissions and leaks from oil and gas facilities, landfills, and livestock facilities. Fine spatial resolutions (< 60 m) offered by facility-scale plume monitors can improve sampling of smaller plumes, with improved sampling in cloudy areas without the need for high spectral resolution (Cusworth et al., 2019; Jongaramrungruang et al., 2021; Thorpe et al., 2023; Wilzewski et al., 2020). Work is needed to

study trade-offs between spectral resolution and precision/accuracy for both CO₂ and CH₄. In general, facility-scale plume monitors offer limited spatial coverage, requiring a constellation of instruments for improved sampling.

High-emission CO₂ point sources such as fossil fuel-fired power plants emitting more than 8 MtCO₂/yr (~900 tCO₂/hr) can be quantified through a combination of high precision (0.25% relative to background, or 1 ppm) and high spatial resolution (~1–10 km) (CEOS-CGMS Joint Working Group on Climate Greenhouse Gas Task Team, 2024). OCO-2, which has a spatial resolution of approximately 2 km and precision of ~1 ppm, meets this requirement. In some cases, OCO-2 could be considered “plume resolving” in its ability to detect point sources with a width in tens of kilometers and a length of potentially hundreds of kilometers, depending on wind speed.

OCO-2 also falls into the class of Global GHG Mappers designed to map CO₂ and CH₄ sources and sinks across small to large regions (~50–500 km). Global GHG Mappers have high spectral and spatial resolution (< 1–2 nm spectral, < 10 km spatial) relative to facility-scale plume monitors, providing the capability to map diffuse area emissions (less intense than point sources, but spread over a larger area), for example, in urban areas and large forested regions. However, our current ability to map GHG concentrations contiguously in time and space, even at low spatial resolution, is limited. First-generation Global GHG Mappers (OCO-2, GOSAT, and OCO-3) sample infrequently (3–16 days) with significant spatial gaps. More recent sensors, such as ESA’s Tropospheric Monitoring Instrument (TROPOMI), ESA’s Greenhouse Gases Observing Satellite-2 (GOSAT-2), and Japan’s Global Observing SATellite for Greenhouse gases and Water cycle (GOSAT-GW) and future sensors, such as the Copernicus Anthropogenic Carbon Dioxide Monitoring constellation (CO2M), sample more frequently (three days) and offer improved spatial mapping through wide swaths, but are limited by coarse footprints. Recent and planned passive and lidar missions including the Carbon Dioxide Monitoring Mission (MicroCarb) (Cansot et al., 2023; launched 2025), CO2M (Meijer et al., 2023), and the Methane Remote Sensing Lidar Mission (MERLIN) (Ehret et al., 2017) are expected to enhance coverage and precision at urban, regional, and global scale.

Current passive sensors are complicated in their sensitivity to altitude. OCO-2 and OCO-3 measure three wavelengths of near-infrared light. An inverse model with many pressure levels is used to infer the relationship between escaping photons and GHG concentration, and the dry molar mixing ratio of CO₂ for the entire air column is reported. GOSAT has a Fourier transform infrared (FTIR) spectrometer that provides additional information to infer CO₂ concentrations on multiple pressure levels, however with insufficient degrees of freedom of signal (DOFs < 2) to discriminate between CO₂ concentrations in the lower versus upper troposphere. The translation of total column concentrations obtained from trace gas

observations into a vertically resolved product is non-trivial and is necessary to separate surface exchange from horizontal transport.

5.2 RESPONDING TO KNOWLEDGE GAPS

For nearly three decades, the GHG in-situ and remote sensing communities have focused on quantifying natural fluxes on land and ocean at monthly to annual time scales and sub-continental to global spatial scales (Figure 5.2). In essence, this permits us to watch the “Earth breathe,” a key goal of the original NASA OCO mission. In the intervening years, other applications have been identified and pursued, namely emissions estimates from point sources or cities. The OCO missions have identified mismatches between what we want to know (attribution of anthropogenic vs. natural carbon flux drivers at Small Region Scale, 10–500 km) versus what we can robustly learn from observations (quantification of net carbon flux at Large Region Scale, > 500 km). The Small Region Scale remains a critical knowledge gap in GHG flux estimation, which would greatly benefit from trace gas profiles, preferably resolving the ABL, mid-troposphere, and upper troposphere. Ultimately, this would bypass the need for significantly improved representation of model transport, but it is not feasible with the cost of current technologies and available budgets.

Multiple pieces of vertical information have enabled direct inference of fluxes. In an aircraft-based mission, Gatti et al. (2021) used the vertical gradient in CO₂ observed from aircraft over the Amazon to directly infer the source vs sink dynamics of the local area across that multiple degrees of freedom are obtained for the lower and upper troposphere. Multi-spectral information from GOSAT and GOSAT-2 has been used to monitor vertical profiles over megacities (Kuze et al., 2022); however, these spectrometers currently do not provide sufficient degrees of freedom (DOFs) and therefore rely on uncertain estimates of covariance between lower and upper partial columns. Thermal observations of CO₂ have been made previously from the Atmospheric Infrared Sounder (AIRS) and Cross-track Infrared Sounder (CrIS), which could, in principle, be combined with short-wave infrared (SWIR) sensors such as OCO-2 to reconstruct vertical profiles (Fu et al., 2016); however, current thermal missions were not conceived or executed with carbon cycle information as a driving priority, and resulting data products are not useful for this purpose. different times of the year. Two simultaneous observations in different

spectral bands (e.g., near infrared and thermal infrared) could be used to generate vertical information, provided

Future satellite missions will need information trade-space analysis to test spectral resolution with the corresponding instrument response function and instrument noise model to understand the vertical information of a combined SWIR/thermal infrared (TIR) instrument. Even after this analysis, simulations are needed to test the required accuracy and precision of the underlying spectroscopic line parameters needed for the radiative transfer calculations to ensure they are able to reproduce the observations and satisfy the overall science requirements. Furthermore, we would need a high-precision requirement for lower troposphere (LT) and free troposphere (FT) partial column observations to improve the flux estimation to determine the spectral resolution for the retrieval algorithm.

Shorter temporal scales also permit information about local fluxes. For example, diurnal observations of the Total Carbon Column Observing Network CO₂ column concentration (TCCON XCO₂) have been shown to reflect local exchange (Keppel-Aleks et al., 2012; Torres et al., 2019). Multiple satellite revisits per day of a single location would permit assessment of the mass change over a given location through finite differencing. This would also make up for a

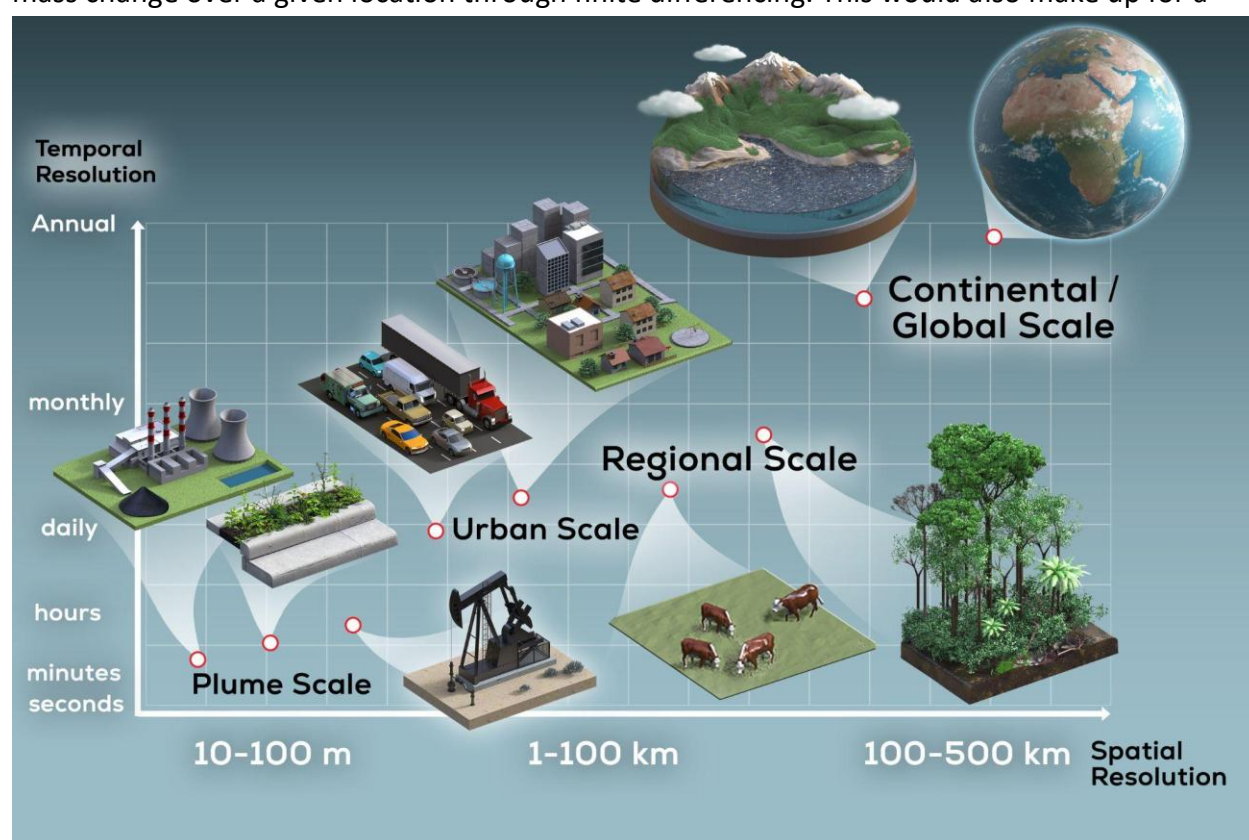


Figure 5.2. Summary of key carbon cycle processes as a function of spatial and temporal scale.
Credit: Keck Institute for Space Studies/Victor Leshyk

lack of data due to clouds or high aerosol loading. When occurring in conjunction with horizontal winds, which could be derived from a feature-tracking approach, the surface flux could be isolated through mass balance.

Ultimately, the new constraints offered by vertical profiles and/or increased sampling frequency will feed into inverse models to address flux information gaps at Small Regional Scale. This additional data load will require ongoing improvements to computational efficiency as flux resolving capacity of inverse models shifts from 100 km scale to 10 km scale, especially for addressing global carbon cycle challenges. This will also require advances in commonly used top-down inversion methods, including 4D variational and ensemble Kalman filter approaches, to be able to accommodate additional observational constraints and covariation of information in vertical (LT vs. upper troposphere [UT]) and temporal (sub-daily to daily) dimensions.

Another way to leverage these data is through mass balance approaches (e.g., Gatti et al., 2021) to independently solve for fluxes over small regions (10s to 100s of km) and to corroborate inverse estimates derived from traditional column integrated data constraints. A third approach for using these data, building off work pioneered by Stephens et al (2007), is to directly validate posterior concentration fields from inverse models, and to benchmark vertical mixing in atmospheric transport models. This third way of leveraging new vertical and sub-daily information will be discussed in more detail in the following sections.

6. ATMOSPHERIC TRANSPORT ERRORS REDUCE THE ACCURACY OF FLUX ESTIMATES

Despite advances in computational resources that enable more complex and higher resolution atmospheric modeling, the trace gas science community is still missing certain key driving variables and processes needed to accurately predict trace gas movements. Through observations targeting key geophysical variables (pressure, temperature, humidity, wind), most modern atmospheric DA systems provide a constraint on advection by horizontal winds, and therefore on divergence/convergence patterns. However, this approach does not address challenges in modeling vertical mixing at subgrid scales, e.g., turbulence and convection, which move trace gases on scales less than 10–50 km and are represented by simplified approximations of high-resolution processes (parameterizations). Hence, biases in surface winds and in the vertical profile of horizontal wind and wind shear remain. Furthermore, to accurately model the exchange of mass and trace gases between the surface and the free troposphere requires accurate modelling of ABL processes. Finally, most atmospheric models

developed for numerical weather prediction (NWP) do not conserve mass, which is problematic when the trace gas inversion community is using these models to track the movement of mass.

6.1 ADVECTION—HORIZONTAL TRANSPORT

Advection that occurs at mesoscales and larger (> 50 km) is generally represented explicitly in transport and NWP models. Horizontal winds advect atmospheric trace gases and aerosols and tend to increase in strength from the ABL through the FT. This means pollution emitted at the surface will generally be transported away from its source faster if the pollutant is transported higher in the troposphere (e.g., by convection).

The interaction between vertical (convection) and horizontal (advection) transport means that, even though models typically simulate horizontal winds reasonably well, errors in vertical transport can lead to estimates of pollutants being advected horizontally at an incorrect rate if their vertical distribution is erroneously simulated.

6.2 PARAMETERIZED CONVECTION—VERTICAL TRANSPORT

A striking example of the impact of uncertainties in the representation of convection in large-scale models is the spread in modeled cloud feedbacks and climate sensitivity. Uncertainties in the vertical mixing of water vapor prevent us from accurately predicting cloudiness and rainfall patterns in the current climate, as well as how these may respond to rising global mean temperatures. These same convective processes, driving vertical mixing and resultant entrainment and detrainment (mixing between clouds and the surrounding environment), are critical for trace gas and moisture modelling.

Previous studies (Schuh et al., 2019; e.g., Stephens et al., 2007) have analyzed the accuracy of vertical mixing and found that modeled vertical GHG profiles may differ significantly from profiles measured by aircraft, and that differences in models' vertical profiles correlate strongly with differences in the distribution of estimated fluxes across large spatial scales. Follow-up work by Gaubert et al., (2019) found some convergence in the distribution of posterior fluxes amongst several models, with a strong correlation with the vertical mixing found only in the Northern Hemisphere summer. Other factors—such as the choice of fossil fuel prior fluxes—were found to play a significant role in the resulting estimates of land and ocean fluxes. This exemplifies the sensitivity of inverse flux estimation to biases in both prior estimates and atmospheric transport.

6.3 ATMOSPHERIC BOUNDARY LAYER: LINKING THE SURFACE TO THE FREE TROPOSPHERE

The ABL is the lowest layer of the troposphere, often around 1–2 km deep during daylight and much shallower at night. Turbulence and convection are responsible for most of

the vertical transport of heat, moisture, momentum, gases and pollution throughout the ABL, and they need to be adequately coupled to surface heterogeneity (Mahrt, 2010).

Even in (deep) convection-resolving or convection-permitting models that run with horizontal grid spacings of a few kilometers or finer, ABL turbulence and shallow (dry and moist) convection must be parameterized. Adequate ABL transport schemes have been developed based on idealized cases (Honnert et al., 2020), but their temporal and spatial behavior needs to be evaluated versus observations, as well as being compared to results produced at the finer resolution of state of the art models.

Another key uncertainty is surface-atmosphere interactions, including surface energy exchange and its interaction with ABL and convective processes. Many studies have focused on oceans and the influence of air-sea interactions on convective and ABL development (Guichard & Couvreux, 2017). Land-atmosphere interactions are generally more complicated, as highly spatially heterogeneous properties of the soil and vegetation exert a significant influence on ABL development (e.g., Osman et al., 2025). It is not well understood how (small-scale) heterogeneity in surface fluxes impact transport, initiation of convection, and the vertical structure of the ABL.

The struggle to accurately simulate the ABL height, especially its evolution throughout the day and night, limits our ability to interpret surface-based measurements and exploit them in the context of flux estimation. While ABL height is most accurately simulated during the afternoon in well-mixed conditions, in-situ trace gas observations from other times of day, especially at night, are typically not used in flux estimation (Maier et al., 2022). This results in the majority of in-situ observations never being used for this purpose.

6.4 MASS CONSERVATION

The interests of atmospheric communities diverge the most when it comes to the importance of mass conservation. Describing an atmosphere with consistent dry air mass, and tracer mixing ratios relative to that dry air mass, is critical when simulating long-lived GHGs. In theory, tracers can be tracked relative to wet air mass, but the fact that water mass is often poorly tracked, especially in parameterized convection schemes, is often the first difficulty a modeler encounters. Mass conservation of tracer mass is potentially even more important for long-term climate simulations, when such errors accumulate over long simulation periods.

In contrast to “free-running” weather forecast or climate models, most transport models need to regularly ingest atmospheric observations to keep their forecast model from deviating too far from reality. As the model state is modified to more closely match the observations, this necessitates, for example, changes in atmospheric mass, density and/or pressure.

In response, tracer mixing ratios (mass of tracers per unit mass of dry air) must either be conserved, implying change in total tracer mass due to the change in dry air mass, or adjusted to the new atmospheric mass fields, causing undesirable “jumps” in dry tracer mixing ratios.

While there is no perfect solution, the general paradigm for the trace gas transport modeler has been to try to maintain global tracer mass while preserving as much of the local dry tracer mixing ratio gradients as possible.

Another fundamental challenge affecting the representation of vertical mixing is the use of tracer transport models to infer the surface carbon exchange. Tracer transport models are typically run separately from a parent general circulation model (GCM), which provides the meteorological drivers. While this can simplify numerical calculations and speed up run time, there is often a requirement to simulate parameterized vertical mixing, including deep convection, using reduced complexity, and often reduced time and space resolution, relative to the parent GCM. For example, the parameterization of multiple subgrid-scale plume structures with different rates of mixing must often be summarized in a chemical transport model (CTM) by a single-plume structure with a single rate of mixing, often running at 5–10 times coarser time and space resolutions (Schuh et al., 2019). The averaging process can lead to bias and significant loss of information (Kawa et al., 2004). The problem is particularly acute when applied to convective mixing and long-lived tracers.

Work is needed to gauge convergence of offline transport within a CTM with transport from the parent GCM as factors relating to (1) representation of convective mass flux (CMF), and (2) spatial and temporal resolution become better aligned. Past work has demonstrated difficulty in characterizing this convergence (Parazoo et al., 2012; Prather et al., 2008), though recent efforts leveraging high time- and space-resolution meteorology via tracer transport modeling systems such as Goddard Earth Observation System-Chemistry High Performance (GCHP: Martin et al., 2022) show promise.

6.5 BENCHMARKING MODEL TRANSPORT

Validation and understanding of the behavior of existing and new model schemes comes from observational data. These are in the form of intermittent field campaigns, as well as long-running atmospheric observatories that provide the key observables at high temporal resolution under a wide range of atmospheric conditions. We detail critical observational data gaps below.

Joint observations of horizontal wind divergence profiles and vertical profiles of trace gas concentrations within a 10-km region, representing the scale of convective processes, will provide an entirely new perspective on vertical trace gas transport to clarify the mixing levels in different meteorological regimes, including the ABL height. Specifically, observations are needed of moist convective updrafts and mesoscale ascent/descent (George et al., 2023),

which may be key to understanding the horizontal patterns of moisture and clouds and the way vertical moisture flux takes place.

The types of observables that are key to improving ABL transport are, to first order, focused on constraining the heat/moisture/momentum balance and vertical exchange in a column. The following set of observations could greatly improve our understanding of, and ability to constrain, ABL transport:

- (1) eddy-covariance measurements of heat, moisture, momentum, and gases,
- (2) profiles of temperature and water vapor from ground-based hyperspectral infrared radiometers,
- (3) profiles of vertical and horizontal wind from ground-based Doppler wind lidar,
- (4) profiles of aerosol backscatter, cloud base height and ABL height from backscatter lidar,
- (5) cloud depth from radar, and
- (6) incoming and outgoing shortwave/longwave radiation fluxes.

Ideally, these measurements should be distributed across multiple locations with different ABL dynamics to sample a spectrum of ABL transport. This can help evaluate tracer transport in the ABL and inform improved parameterizations.

Errors in the simulation of vertical mixing are exemplified by the difficulty that models often have in accurately simulating the tropopause height and the age of air in the stratosphere (Randel & Jensen, 2013). Numerous model intercomparisons have highlighted the persistent challenge faced by tracer transport models (over multiple decades) in simulating the exchange of tracers such as sulfur hexafluoride (SF₆), CO₂ and CH₄ between the ABL and FT, leading to systematic errors in the magnitude of vertical tracer gradients (Denning et al., 1999; Patra et al., 2011; Schuh & Jacobson, 2023; e.g., Stephens et al., 2007). Vertical mixing errors become amplified for long-lived trace gases such as CO₂ and CH₄ and are difficult to track down due to changing and poorly quantified surface sources and sinks.

To summarize, combined meteorological and trace gas observations would provide a rich and urgently needed dataset to better understand the prevalence of convective mixing and its role in weather, climate, and transport of trace gases. Characterizing vertical mixing—a key challenge identified by the cloud-climate community—would help validate the vertical mass flux in a new era of storm-resolving models. Better vertical mixing estimates would also provide horizontal divergence profiles that can be assimilated into atmospheric models to better meet air quality and GHG application needs.

7. SYNTHESIS

The simulation and observation of vertical mixing and trace gas vertical structure are key gaps for connecting trace gas data to surface fluxes at multiple scales (Chapter 3). It will be necessary to advance coordinated observational and modeling approaches to address the vertical mixing problem. Several planned satellite missions will use active remote sensing to estimate vertical mixing in clouds, which could, in principle, help constrain forward and inverse simulations of trace gas transport. However, uncertainties in the timing of these missions, along with their incomplete spatial and temporal coverage, will limit their use in data assimilation (DA) and for evaluation and improvement of models.

Investigating the carbon cycle at all scales is necessary to quantify critical fluxes between the Earth system and the atmosphere and to develop process-based models that can confront conclusions made at larger scales. Scale determines the nature of the necessary action.

At large regional scale: We prioritize large regions that need to be understood either because of natural or anthropogenic carbon fluxes that are not well known or due to rapid change that is critical to the global balance of the carbon cycle (e.g., the arctic tundra).

At small regional scale: We prioritize areas that are not well characterized and likely contribute an outsized influence on the carbon cycle. These small regions emit large fractions of the total GHG flux and, when quantified, will reduce uncertainties significantly (e.g., oil and gas basins).

At local scale: We prioritize point sources that can be used to test and improve inventories and process-based models (e.g., large cities). The improved process handling can in turn improve upscaled processes at larger scales.

Only at very local scales are co-located measurements of trace gases and winds beneficial in driving innovation. Otherwise, coordinating measurements across multiple platforms can generate applicable data. ABL height, CMF, and trace gas vertical profiles, combined with model development leveraging ABL and CMF data and model validation against trace gas profiles, should be top priorities.

7.1 THE PROBLEM

Inferring surface sources and sinks from atmospheric trace gas data depends on multiple factors including, but not limited to, observational coverage and atmospheric transport modeling as discussed in Sections 4–6. Other key factors include inversion methodology (e.g., variational vs. ensemble Kalman filter approaches), prior estimates of carbon flux and

associated uncertainties (e.g., process models vs. carbon cycle DA systems), and evaluation strategies (direct comparison to eddy covariance data vs. indirect comparison to independent trace gas data).

Single-instrument science teams support development of many of the elements going into top-down and bottom-up flux estimation methods for individual instruments and observables, but these teams do not typically address the fundamental problem of transport error associated with weather and climate centers. The meteorological community often develops models and benchmarks meteorological fields without considering their impact on atmospheric transport accuracy, despite their widespread use in trace gas studies. Similarly, the design of meteorological remote sensing satellites rarely prioritizes their potential to enhance atmospheric transport modeling, even though uncertainties in wind fields represent the largest source of error in estimating large point-source emissions.

Research and analysis programs like OCO and MAP are insufficient in scope for addressing a fundamentally interdisciplinary problem, and insufficient in duration to address a long-term (5–10 year) research challenge. This gap leads to substantial uncertainties in inferred sources and sinks, even in regions where trace gas observations are abundant. To address these challenges, we advocate for a sustained program that fosters long-term collaboration between meteorological and trace gas communities. Such an initiative would enhance the use of the growing suite of remote sensing observations to improve atmospheric transport modeling and ensure that future meteorological satellite missions are designed with the goal of advancing trace gas transport accuracy.

7.2 DESIGNING A PROGRAM TO INTEGRATE COMMUNITIES

Surface fluxes of trace gases (e.g., of CO₂ and CH₄) are important to understand ecosystem processes and climate feedbacks. While these fluxes cannot be measured globally, accurate and high-precision in-situ and space-based atmospheric measurements can be used to constrain surface fluxes. These measurements are discrete and sparse and are linked to surface flux using simulations of atmospheric transport. Accurate representation of atmospheric transport therefore is critical in producing bias-free surface flux estimates. Atmospheric transport errors are difficult to diagnose as they are usually convoluted with flux errors (Schuh et al., 2019). This problem is exacerbated due to the lack of measurements of winds and planetary boundary layer height.

A coordinated ABL and GHG mission could greatly benefit both NWP and GHG communities. For the GHG community, ABL and wind speed measurements would enable better characterization of atmospheric transport model errors, and allow for potentially constraining partial columns, both of which will considerably reduce flux errors. Given the paucity of ABL measurements, increased wind and ABL would help the NWP community in

reducing model errors and improving weather forecasts. Another synergistic effect could be in the domain of seasonal weather forecasting. For example, accurate representation of CO₂ fluxes (from increased CO₂ sampling) would allow for a better representation of the biosphere and potentially improve drought forecasting via better estimates of energy partitioning from vegetated ecosystems.

We highlight three pathways by which novel, independent surface- and space-based observations of vertical mixing (ABL height, horizontal winds, convective mass flux) can help address transport errors, helping to improve NWP performance while also improving inverse estimates of surface trace gas fluxes.

First, these measurements can be compared directly to output from NWP models to evaluate the magnitude and depth of vertical mixing in different regions and latitudes. This approach can guide development of transport models to meet the needs of NWP and inverse modeling communities and help minimize model structural errors and regional biases.

Second, as discussed in Section 4.3, DA can provide a near-term approach for improving vertical transport by providing constraints on horizontal and vertical winds and ABL height.

Finally, observations can be used to quantify random and systematic errors in transport models, information that can then be used to develop realistic model ensembles. Transport ensembles enable transport uncertainty to be translated into more realistic uncertainties in flux estimates.

It may be possible to exploit the existing and potential connections among various models to improve the joint representation of dynamics and trace gas fluxes and concentrations. That said, even when models are coupled, coupled DA remains a significant challenge. We also note the terrestrial ecology and the ocean biogeochemistry and biology communities have traditionally been represented by separate program elements within NASA and other US federal agencies and have been responsible in part for developing robust prior estimates of carbon exchange in natural land and ocean systems from models and remote sensing. It is unclear how the current reorganization of program elements could lead to new relationships among previously siloed research and applications areas. Ensuring logical connections among previously distinct areas of funding is a critical component of this proposed coordinated community program.

7.3 DESIGNING MODELS TO INTEGRATE DATASETS

The increasing volume of satellite data and resolution of transport models can improve the accuracy and scale of carbon flux inversion constraints, but presents a challenge due to computational and structural limitations. Harnessing advanced machine learning, DA, and computational techniques is crucial for overcoming these limitations. Achieving this requires a

dedicated program that fosters collaboration between the meteorological and trace gas research communities and experts in machine learning and high-performance computing.

In terms of computational limitations, operational carbon flux inversion systems providing carbon flux information at low latency are needed to better inform carbon management efforts. For this, we should seek to take advantage of new numerical analysis approaches for multiscale modeling to reduce the cost of solving nonlinear inverse problems (e.g., multipole methods, Hu & Dance, 2024) and assess how they can improve current practices.

In terms of structural limitations, the current generation of inventories, mechanistic models and atmospheric inversions are limited in terms of the observations they can assimilate, both in terms of type (e.g., atmospheric observations, economic data, land surface properties) and in terms of the source (e.g., many atmospheric inverse models can only leverage in-situ observations and/or observations from a single GHG satellite). In addition, they are limited in the representation of the relationship among variables (e.g., the functional forms used to represent key processes) and in the parameterization of these processes. As a result, models tend to have limited skill when estimates are compared against new observation types, such as when mechanistic models are evaluated against atmospheric constraints (Foster et al., 2024). Atmospheric constraints can also provide direct insights into mechanisms controlling carbon fluxes (e.g., Sun et al., 2023). There is, therefore, a large opportunity to develop modeling frameworks that can more seamlessly incorporate a broader diversity of observations.

Leveraging machine learning for model development provides an opportunity to address both limitations, because it can handle a larger set of assimilated variables (Wang et al., 2024), optimize the use of satellite observations in DA models by using information that typically is discarded due to correlated errors (Howard et al., 2024), and can increase the utility of observations to constrain, improve models, develop better parameterizations (Geer, 2021). Machine learning can also be combined with DA in iterative methods to correct errors in the underlying models (Farchi et al., 2021). Machine learning models for weather forecasting (Lam et al., 2023) are already being trained at scale to provide fast weather forecasts based on historical data.

Some models called foundation models (Bodnar et al., 2025) serve both as a starting point for researchers to train more task-specific models on smaller datasets through a process called fine-tuning and as feature extractors for downstream tasks. Foundation models can be thought of as distilled representations of the datasets they were trained on. Practitioners have observed that deep neural networks learn patterns and features of data that are useful beyond the tasks they were trained on, allowing foundation models to be adapted to solve new problems with relative ease. Because foundation models encapsulate large amounts of information from their training data, they offer a natural approach to DA by acting as proxies

for the large observational datasets they were trained on. While training foundation models can be computationally expensive, using them is relatively cheap, offering a promising approach for integrating extensive historical data into transport models. Several new modeling efforts (e.g., Earth AI and AlphaEarth) have already preprocessed petabytes of data.

In addition to foundation models, another active area of machine learning research focuses on constructing scientific models that directly integrate and utilize large datasets to improve predictions and understanding in various domains. Physics-informed machine learning (Brunton & Kutz, 2022; Kochkov et al., 2024) is dedicated to building machine learning systems that incorporate both known physical laws and data to solve problems. Additionally, diffusion and flow-based generative models are based on principles from fluid dynamics and can potentially be a useful tool for developing transport models that adhere to physics while incorporating vast amounts of data.

7.4 BENCHMARKING SUCCESS

A major challenge in applying top-down carbon source and sink estimates to scientific and policy applications is the lack of rigorous benchmarking across scales.

The primary exception is at local scales (1–2 km²), where significant progress has been made through the use of eddy covariance data to evaluate net and gross carbon exchange across a range of ecosystems (forest, agricultural, wetlands), temporal scales (diurnal to decadal), and regions including Arctic and tropical regions (Baldocchi, 2020; McNicol et al., 2023; Virkkala et al., 2021). Likewise, controlled-release experiments have seen wide use in the evaluation of large point-source estimates from aircraft, particularly for CH₄ (Thorpe et al., 2016). However, challenges remain, including sparse flux tower coverage of tropical regions, detection of intermittent point source emissions, and minimizing false negatives.

Evaluation of carbon flux at small (10–500 km) to large (> 500 km) regional scale has traditionally relied on comparison of estimated carbon fluxes to independent observations from towers, aircraft, and upward-looking spectrometers through tracer transport model simulations. Here, estimated carbon fluxes refers to fluxes optimized against tower and/or spaceborne trace gas data, and independent observations refers to data withheld from assimilation in the inverse model.

Airborne GHG profiles from research and commercial aircraft can provide an extremely valuable source of information for independent evaluation of inversion-based flux estimates and can help to diagnose atmospheric transport model errors that can lead to flux estimation bias. For example, the NOAA Global Monitoring Laboratory (GML) has sampled atmospheric GHG profiles up to 12 km altitude every 2–3 weeks using light aircraft at a dozen sites across the US, Canada, Rarotonga, Brazil, and Africa for over a decade. Likewise, the recent National Observations of Greenhouse gasses Aircraft Profiles (NOGAP) 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. Ground-based spectrometers from networks such as Total Carbon Column Observing Network (TCCON) provide accurate and precise measurements of column-average abundance of multiple GHG species and offer continuous sampling of GHG species throughout daylight hours with clear skies (Wunch et al., 2017). Finally, long-term ground-based GHG measurements from globally coordinated networks can help evaluate top-down fluxes globally, regionally, and locally. Long-running background sites and tall tower networks are critical for monitoring and constraining global and regional trends, respectively, in CO₂ and CH₄ budgets (Bruhwiler et al., 2014; Byrne et al., 2023; Peters et al., 2007).

We need to leverage different approaches for using complementary data beyond the primary GHG concentration for determining source attribution of trace gas emissions depending on the gas and scale of interest. Atmospheric tracers are used to identify and separate sources and sinks, only some of which are observed from space or robust surface networks. For the example of tracking atmospheric carbon, nitrogen oxides (NO_x) are produced from any hot/combustion reaction, CO is produced during the incomplete combustion of carbon-rich fuels, while hydrogen cyanide (HCN) is commonly associated with wildfire activity (Byrne et al., 2024; Park et al., 2021). Photosynthesis and other biogenic processes can be tracked through measurements of solar-induced fluorescence (SIF) and carbonyl sulfide (Parazoo et al., 2021; Whelan et al., 2020), both close correlates of photosynthesis. Oil and gas operations are often monitored using co-emitted tracers like ethane (C₂H₆) and CH₄ (Franco et al., 2016; Tribby et al., 2022), while agriculture-related emissions are often tracked with ammonia (NH₃). Besides proxies for probing the atmosphere, other data describing the land surface such as high-resolution land cover types, biomass, and burned area information are critical for understanding biological and fire activities (Sands et al., 2024).

7.5 RECOMMENDATION: COORDINATED METEOROLOGY AND GHG PROGRAM

With the growing availability of satellite, surface, and aircraft trace gas observations, there is immense potential for these data to enhance Monitoring, Measurement, Reporting, and Verification (MMRV) programs and improve our understanding of the global carbon cycle. However, fully realizing this potential depends on how effectively the scientific community can integrate and utilize these observations within inverse modeling systems.

To maximize the scientific and policy utility of global and regional top-down inversion results, we call for a coordinated effort to develop a comprehensive benchmarking program, leveraging GHG and complementary data, that systematically evaluates and attributes flux estimates and their uncertainties across scales, from individual point sources to global assessments.

A coordinated meteorology and atmospheric composition program focused on community science, which fosters collaboration among relevant research communities and ensures that all essential elements for inferring fluxes from trace gas observations are continuously improved, is critical for sustained, long-term improvements to carbon source and sink quantification and improved weather prediction.

A key component of this approach is the development of testbeds to inform vertical mixing, building off programs such as the European-led Carbon Atmospheric Tracer Research to Improve Numerics and Evaluate (CATRINE) project.³ The CATRINE project aims to enhance the accuracy of atmospheric tracer models for effective emissions monitoring. CATRINE has recently proposed a protocol for tracer transport simulations at high resolution ($< 1^\circ \times 1^\circ$) targeting anthropogenic signals. A similar approach has been taken leveraging output from the OCO Model Intercomparison Project (OCO-MIP; Byrne et al., 2023) to identify uncertainties in parametric moist convection and boundary-layer diffusivity (Schuh & Jacobson, 2023).

While intercomparisons are essential for identifying vertical mixing errors and benchmarking high-performing transport models, they do not address the underlying issue relating to the quality of wind information. We have called for more dedicated efforts at climate and weather modeling offices to assimilate atmospheric wind data into models for improved data reanalysis. Another option, proposed by Chevallier et al. (2025), is coupling atmospheric inversion systems with NWP models. For example, the European Centre for Medium-Range Weather Forecasts (ECMWF) has focused on the development of anthropogenic GHG emissions monitoring and verification support capacity. The Global Modeling and Assimilation Office (GMAO) has undertaken a similar effort with a two-year, global, non-hydrostatic mesoscale simulation nature run, including simulation of CO₂ from natural and anthropogenic sources⁴. These efforts highlight leadership at key modeling centers and offer a pathway for broader community collaboration.

These recommendations are supported by the Decadal Survey Midterm Assessment, which recommended that agencies such as NASA and NOAA seek interdisciplinary engagement from the Earth system modeling community, and encourage engagement of scientists working on weather and air quality prediction at sub-seasonal to decadal scales, to more fully leverage Earth observations to advance model parameterization and predictions.

³ <https://www.catriner-project.eu/>

⁴ <https://gmao.gsfc.nasa.gov/gmao-products/7km-g5nr/>

APPENDIX A: ACRONYMS

ABL – Atmospheric Boundary Layer

AGAGE - Advanced Global Atmospheric Gases Experiment

AMV – Atmospheric Motion Vector

AOS – Atmosphere Observing System

CATRINE - Carbon Atmospheric Tracer Research to Improve Numerics and Evaluate

CCUS - Carbon, Capture, Utilization and Storage

CDR – Carbon Dioxide Removal

CEOS-CGMS – Committee on Earth Observations Satellites – Coordination Group for Meteorological Satellites

CH₄ – Methane

CMF - Convective Mass Flux

CO - Carbon Monoxide

CO₂ – Carbon Dioxide

COCCON - COllaborative Carbon Column Observing Network

CTM – Chemistry Transport Model

DA – Data Assimilation

DWL – Doppler Wind Lidar

ECMWF - European Centre for Medium-Range Weather Forecasts

EMIT– Earth Surface Mineral Dust Source Investigation

ESA – European Space Agency

EUMETSAT – European Organisation for the Exploitation of Meteorological Satellites

F-NBS - Forest-focused Nature-Based Solutions

FT - Free Troposphere

FTIR - Fourier-Transform InfraRed Spectroscopy

GCM - General Circulation Model

GEO – Geostationary Orbit

GGGRN - The NOAA Global Greenhouse Gas Reference Network

GHG – Greenhouse Gases

GMAO - Global Modeling and Assimilation Office

GOSAT - Greenhouse gases Observing SATellite

ICOS - Integrated Carbon Observation System

IME - Integrated Mass Enhancement

INCUS - Investigation of Convective Updrafts

KISS - Keck Institute for Space Studies

LEO - Low Earth Orbit

LES - Large Eddy Simulation

LT – Lower Troposphere

MAP – Modeling, Analysis, and Prediction

MMRV – Measurement, Monitoring, Reporting, and Verification

NASA – National Aeronautics and Space Administration

NbCS - Nature-based climate solutions

NDADC - Network for the Detection of Atmospheric Composition Change

NDCs - Nationally Determined Contributions

NOAA – National Oceanic and Atmospheric Administration

NO_x - Nitrogen Oxides

NWP – Numerical Weather Prediction

OCO-2 - Orbiting Carbon Observatory 2

OCO-MIP – Orbiting Carbon Observatory Model Intercomparison Project

OECD - Organisation for Economic Co-operation and Development

TCCON – Total Carbon Column Observing Network

UNFCCC - United Nations Framework Convention on Climate Change

UT – Upper Troposphere

WIVERN - WInd VElocity Radar Nephoscope

APPENDIX B: REFERENCES

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APPENDIX C: LIST OF ILLUSTRATIONS

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APPENDIX D: TABLE 4.1 REFERENCES

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