

The Importance of Surface-Atmosphere Interactions for a Mission focused on the Planetary Boundary Layer

Authored by the PBL DSI Surface Interactions Working Group

1. Executive summary

The NASA Planetary Boundary Layer (PBL) mission will be transformational to advancing PBL science and applications. Such a mission will require a significant focus on the key connections of the PBL to the surface and to the lower troposphere across time (diurnal to interannual) as well as across space from point-to-pixel-to-planet. This includes acknowledging and integrating the dynamics of the Earth *surface* and especially how the influence of these *surface dynamics* feed back to the PBL changes over time and space. These processes can have significant impacts on a variety of natural hazards, including extreme precipitation leading to floods and landslides, droughts that affect the water management and agriculture sectors, as well as wildfires, dust storms, and heatwaves that influence public health and wealth. Therefore, improvement in understanding the PBL and especially its interactions with the surface has direct consequences for decision makers across sectors as prioritized under NASA's Earth Science to Action Strategy.

Here, we describe priorities and strategies for integrating surface interactions with the atmosphere to guide requirements and priorities for a future PBL mission. This description includes how PBL measurements will address critical science questions pertaining to surface-atmosphere interactions, coastal and ocean systems, hydrologic cycling, and the cryosphere-atmosphere domain. We detail how existing and emerging PBL technologies across platforms (i.e., surface, air, and space) and scales (spatial and temporal) provide insights into the role of the surface properties on PBL retrievals and inform PBL technology needs for understanding the key variables that, within the surface-atmosphere interactions, influence weather and climate.

2. Introduction:

2.1 Goals, challenges and opportunities of PBL retrievals over heterogeneous surfaces

The planetary boundary layer (PBL) is a critical region of the lower atmosphere that is directly influenced by Earth's surface through solar radiation absorption and reflection, thermal emission, momentum transfer of energy (via friction), and the transfer of water and energy between the surface and atmosphere. The PBL is thus the connective tissue that links surface properties to the troposphere and its complex processes influence diurnal to subseasonal-to-seasonal (S2S) scales of weather and Earth system variability (Santanello et al. 2018). It is widely acknowledged that improving the spatiotemporal characterization of the structure and diurnal evolution of the PBL is essential to address important gaps in our process-level understanding of surface-atmosphere couplings and feedbacks in the Earth system (e.g. Green et al., 2017; Helbig et al. 2021; Wulfmeyer et al. 2018). Advancing our ability to observe and model the PBL also has important societal benefits and direct implications for weather and air quality forecasts. Examples include improvements in severe weather prediction, cloud and precipitation modeling, forecasting extremes (e.g. floods and droughts), monitoring of aerosol

dispersion, optimization of wind energy, developing sustainable agricultural practices, and the evaluation of bio-geoengineering approaches. Increasing the fidelity of PBL observations in space and time would also have direct impacts on hydrologic and biospheric sciences and applications, including improved understanding of the water and energy cycles, which would address urgent needs for resource management and food production, and fire risk and weather prediction.

To fully achieve these societal benefits, we must address the considerable gaps that remain in our ability to observe and model the processes and scales that regulate the PBL, particularly over complex terrain and heterogeneous surfaces (e.g. coastal zones, transitions between urban and rural landscapes, agricultural landscapes). Because of the urgent requirement to increase the fidelity of PBL retrievals from space, particularly over land, the National Academies of Sciences, Engineering and Medicine (NASEM) 2017-2027 decadal survey for Earth Science and Applications from Space (NASEM, 2018) highlighted the need for routine PBL measurements from space coupled with continued support for critical ground networks (such as the GEWEX Land-Atmosphere Feedback Observatories, GLAFOs, Wulfmeyer et al. 2020; DOE ARM including AMF3-BNF, Kuang et al. 2023). A sub-orbital component was also requested focusing on process studies, filling observational gaps (e.g. momentum), calibration/validation and scaling, and modeling capabilities that could provide a complete global PBL observing system. In this context, the PBL was designated as an Incubation Targeted Observable, with vertical profiles of temperature (T) and humidity (q) along with a measurement of PBL height (PBLH) as high priorities under specific observational requirements (Teixeira et al. 2025).

Following these recommendations and supported by a wide range of detailed studies on viable technologies, scales, and approaches from the surface to space, substantial insights have been gained into the role of surface properties in PBL dynamics and thermodynamics. For example, there is renewed recognition of the role of surface-atmosphere interactions and near-surface stability in shaping the diurnal evolution of the PBL (e.g. Santanello et al. 2018), including the influence of soil moisture on coupling strength and the role of diurnal fluxes (Santanello et al. 2019). Furthermore, biomass burning and fires create complex interactions in the PBL that can affect convection, cloud microphysics, rainfall patterns and weather (e.g. Lareau et al., 2022; Peterson et al., 2021), but current observational constraints limit our ability to study these interactions and surface feedbacks. Recent campaigns and detailed process studies show that substantial challenges remain in resolving key coastal processes that can drive PBL heterogeneity across critical land-water interfaces. These processes impact air quality and human health, including through the role of coastal communities and vegetation biogenic emissions on the PBL (e.g. Sullivan et al., 2023). Furthermore, studies and campaigns in colder climates have demonstrated the influence of sea ice and seasonality on uncertainties in PBL retrievals and modeled estimates (e.g. Xi et al. 2024). Together, these new insights and the gaps they highlight demonstrate the need (a) to improve the representation of PBL processes in models to better capture the influence of surface conditions, ocean-atmosphere couplings, and the impacts of surface dynamics and changes on the PBL and related processes, (b) to address current observational limitations, and (c) to advance both theoretical and practical approaches for analyzing and modeling land-atmosphere coupling. These studies also highlight the significant challenges facing

a future PBL observing system which would ideally need to resolve the scales of critical processes (e.g. 1-3 hourly, 100m to 10km) shaping the coupling between weather and the surface (Teixeira et al. 2025; Sullivan et al. 2023).

The purpose of this white paper is to motivate, detail, and make recommendations regarding how a proposed NASA PBL mission would obtain better observations of temperature (T), humidity (q), and PBLH. It also discusses how addressing current scientific gaps enables improved applications for societal benefit. Our focus is specifically on the PBL's interactions with the surface and complements two other PBL white papers focused on clouds and convection.

2.2 Current state of observations from surface to space

Within the existing Program of Record (PoR), observing systems for the PBL that includes surface networks and orbital platforms provide valuable insights into the thermodynamic structure and variability of the PBL, offering key information for both scientific and operational applications. While these measurements capture important aspects of T and q profiles, PBLH, as well as surface properties, each observing approach has its own limitations in sampling or resolution, resulting in observational gaps. The gaps are particularly prevalent over heterogeneous land surfaces and large portions of the oceans and cryosphere.

Surface meteorological observations are typically measured worldwide on an hourly basis, but they are limited to specific ground networks and meteorological stations (e.g. DOE ARM, ASOS, MPLnet, the European profiling network E-Profile (<https://e-profile.eu/>), the New York Mesonet <https://www.nysmesonet.org/>, etc.). The WMO Global Observing System of ~900 twice-daily radiosonde stations (i.e. the backbone of NWP since its infancy) provides excellent vertical resolution, as fine as ~10 meters in the PBL, but lacks horizontal and temporal coverage. Another widely used and relatively new technique of in-situ measurements of PBL thermodynamics is commercial aircraft data (AMDAR, Avşar 2018; Zhang et al. 2019). These measurements capture the diurnal evolution of the PBL, but observations are restricted to airport locations.

Recent developments in new sub-orbital technologies demonstrate the value of simultaneous, multi-instrument measurements of the PBL. These measurements can directly capture PBL profiles of T and q and PBLH at finer spatial resolutions than from spaceborne infrared and microwave spectra and could increase the information content of IR and MW sounders from data fusion/joint retrievals (e.g. Turner and Lohnert. 2021, Gambacorta et al., 2024; Gambacorta et al., 2025a). While these sub-orbital campaigns are providing calibration and validation opportunities for spaceborne PBL retrieval algorithms (e.g., Nicholls et al., 2025), they do not provide sustained measurements in time and space due to their single or multiple overpasses over specific seasons or regimes.

Satellites involve a trade-off between spatial and temporal resolution. The current state of the art infrared (IR) sensors allow the retrieval of T and q profiles with ~14 km of horizontal resolution and ~1-2 km of vertical resolution, only under clear or partially cloudy sky conditions. While most clouds are opaque in the IR due to the presence of liquid droplets and ice particles, they are partially transparent to microwave (MW) radiation, allowing for all-sky T and q profile retrievals, albeit with

coarser horizontal and vertical resolution compared with hyperspectral IR. Nevertheless, MW and IR passive remote sensing are attenuated by cloud cover and largely confounded by surface heterogeneous properties and fluxes (e.g. Wulfmeyer et al. 2015). As such, remotely sensed atmospheric information has been predominantly constrained to that above the PBL (NASEM, 2018). For example, numerical weather prediction data assimilation systems often neglect surface sensitive channels over land. Furthermore, NASA and NOAA operational retrievals from passive sensors suffer from large uncertainties in the presence of sharp gradients in PBL thermodynamic structure. Uncertainties related to heterogeneity in surface type and spectral emissivity propagate into surface temperature and PBL atmospheric temperature and water vapor retrieval errors, hindering the capability to fully resolve PBL vertical structure. By carefully selecting channels that are mostly transparent to atmospheric absorption (so called “window” channels), one could write the physical relationship linking brightness temperature, surface emissivity and surface temperature as in equation 1, momentarily neglecting, for simplicity, the atmospheric term $A(\nu)$, the reflecting term $R(\nu)$, the downwelling and reflecting term $D(\nu)$ and the scattering term $S(\nu)$.

$$BT(\nu) = \varepsilon(\nu) \cdot T_s \cdot \tau_{total}(\nu) + A(\nu) + R(\nu) + S(\nu) \quad (\text{eq 1})$$

Where:

- ν represents the sensor measurement frequency
- $\varepsilon(\nu)$ represents emissivity as a function of frequency
- T_s represents surface temperature
- τ_{total} represents total surface to top of atmosphere transmittance.

Surface emissivity over land is strongly variable, dependent on a host of factors including surface type, surface moisture, and spectral frequency (e.g., Baldridge et al., 1999; Huang et al., 2016). As observed in equation one, even small errors in surface emissivity of just a few percent can cause errors of several degrees Kelvin in retrieved surface temperature, which then propagates into retrieval uncertainties in PBL T and q.

Improvements in the characterization of surface emissivity have been hindered by the lack of in situ data and experiments designed to improve physical modeling and, as in the case of MW sounding, the lack of information content on emissivity variability across surface types. While infrared sensors have continuously improved in spectral coverage and resolution (e.g., L’Ecuyer et al., 2021; Zheng et al., 2024), microwave sensors have remained constrained by the size, weight and power requirements of radiofrequency technology. Recent developments in photonic integrated circuits are poised to revolutionize passive MW sounding technology and enable hyperspectral MW sounding from space, as proposed by the Advanced Ultra-high Resolution Optical and Radiofrequency (AURORA) Pathfinder (Gambacorta et al., 2025b; Gambini et al., 2024, Torres et al., 2025).

Even with improved technology, we still face the challenge of improving surface classification techniques, emissivity modeling, and cloud geophysical constraints to help disentangle the interfering

signals in observations. These improvements would enable an all-sky, all-surface PBL retrieval product while maturing the science readiness level needed to support novel technologies. Turner and Lohnert (2021) and Gambacorta et al. (2025a) have demonstrated improved PBL thermodynamic sounding by combining passive and active measurements (i.e., differential absorption lidar and backscatter lidar) in the presence of clouds and aerosols. Surface classification (e.g., type, structure, roughness, function, dynamics, etc.) and emissivity modeling can be improved via intensive, dedicated field campaigns that characterize multiple surface scenes with co-registered brightness temperature measurements. Including the physical drivers of variation is also essential for a physics-based approach that can also account for surface properties. Regardless, a sustained, operational network of ground observations is recommended to ensure accurate initialization during routine data assimilation and retrieval processing.

Intensive ground-based facilities (e.g., ARM SGP in Oklahoma, Sisterson et al., 2016; LAFO in Germany, Späth et al., 2023), dedicated airborne campaigns (e.g., WH²yMSIE, Gambacorta et al., 2024; ACTIVATE, Sorooshian et al., 2025), and field programs (e.g., TOGA COARE; Webster and Lukas, 1992; DYNAMO, Yoneyama et al., 2013; PECAN, Geerts et al., 2017; MOSAiC, Shupe et al., 2022) all provide excellent opportunities to perform co-registered all-surface and all-sky experiments aimed at developing and validating improved technologies and data fusion approaches.

3. PBL Science: the role of the surface in the PBL

3.1 PBL Surface Interaction Processes

The planetary boundary layer is formed by the interaction of the troposphere with Earth's surface. The surface influences the PBL thermodynamically via exchanges of water and energy with the surface (sensible and latent heat fluxes) and between the PBL and the lower free troposphere via entrainment. The surface also exchanges mass, momentum, and energy with the lower troposphere mechanically through near-surface wind shear, where the surface exerts a drag force on the movement of air, and creates eddies that influence the lower atmosphere. As such, the Earth's surface is fundamental to PBL processes.

The surface also modulates the magnitude of these surface-based dynamic and thermodynamic influences. The partitioning of sensible and latent heat fluxes and hence the PBL structure and evolution depends strongly on surface types (e.g., vegetated land, bare land, urban land cover, ice, inland water bodies, and ocean) and surface properties and dynamics (e.g., soil moisture, roughness, displacement, turbulence). For example, drier soils result in a relative shift to increased partitioning of incoming solar energy into sensible rather than latent heat flux, and a generally deeper boundary layer (Molod et al., 2019; Lin et al. 2022). Land cover structure and heterogeneity induce not only turbulent but also dispersive fluxes therefore altering the conductance of water and energy fluxes from the surface to the atmosphere. Horizontal gradients of land surface properties, including land cover changes and rainfall-induced soil moisture changes, can cause localized mesoscale circulations which can propagate into the lower troposphere (Eder et al. 2015; Simon et al. 2021; Paleri et al. 2025; Taylor et al. 2012).

Radiative effects also create surface-atmosphere interactions. More solar radiation absorbed by the surface, whether due to increased incident sunlight or lower albedo, raises the surface temperature and drives sensible heat flux. Variability in surface reflection of incoming shortwave radiation (through surface albedo) due to soil, vegetation, snow, water, and ice color and structure can alter how much Earth's surface warms. Additionally, the incident solar radiation that drives surface-atmosphere interactions is modulated considerably by clouds and aerosol particles in the PBL, which themselves are partly influenced by surface sensible and latent heat fluxes. Aerosols in particular can alter the thermodynamic regime of the lower atmosphere and impact the evolution of the PBL. For example, aerosols directly influence vertical heat transfer and fluxes, which can alter entrainment into the upper boundary layer, and reduce incident radiation on the surface, which can reduce sensible and latent heat fluxes (e.g., Liu et al. 2019; Molod et al. 2019; Su et al. 2020; Zhang et al. 2022; Pal et al. 2025).

Surface-atmosphere interactions are challenging to observe and model due to the interactive effects of water and energy fluxes together with the spatio-temporal dynamics associated with biophysical processes and surface heterogeneity. Earth's surfaces span diverse environments from land, sparsely vegetated inland to coastal and ocean systems, to polar and ice-covered conditions; they act across a broad range of temporal and spatial scales. For example, surface-influenced warming and the corresponding evolution of turbulent kinetic energy (TKE) regulates the diurnal cycle of PBLH. Heterogeneity of surface soil and vegetation moisture and land cover at kilometer scales can generate horizontal moisture and energy gradients that can trigger and modulate convection (Taylor et al. 2011, Simon et al. 2021). At 10s of meter scales, vegetation heterogeneity can also modulate conductance and latent heat flux (Paleri et al. 2025). Such processes occurring at these fine spatial and temporal scales place high demands on a PBL mission. This is in addition to the range of processes involved in these surface-atmosphere interactions (Santanello et al., 2018), which require a broad range of spectral bands and observing technologies to characterize and monitor (Table 1).

Due to a lack of direct observations of latent and sensible heat fluxes and T and q profiles at scale, fundamental debates continue about how surface moisture and structure alters PBL evolution and consequent convection (e.g. Campbell et al., 2019). This includes whether more soil moisture and/or different vegetation types enhance or suppress convectively driven extreme rainfall. This also includes how surface-atmosphere conditions enhance or suppress hot and dry conditions, with implications for droughts and heatwaves (e.g., Zhou et al. 2019). For example, recent modeling studies demonstrate the role of vegetation phenology and shifting seasonal patterns in altering surface fluxes and the critical role these processes could play on seasonal and future PBL dynamics (e.g. X. Li et al., 2023). Higher resolution PBLH retrievals (100m or finer) are needed to quantify these impacts. Similarly, Tian et al. (2024) demonstrated that uncertainties in land-atmosphere coupling strength can lead to underestimation of convective precipitation, while an improved understanding of the PBL in complex surface regimes could significantly reduce these uncertainties.

3.2 PBL Science Questions

PBL Surface Interaction focused science questions are as follows:

1. How do diurnal surface energy exchanges govern the coupled evolution of PBL humidity,

- thermodynamic structure, and air pollutants (and vice-versa)?
2. What is the impact of surface heterogeneity on the PBL thermodynamic structure and convective initiation?
 3. How do PBL structure and evolution modulate local and remote processes and feedbacks that regulate hydrological and climatic extremes (such as drought, flood, and heatwaves)?

Addressing these critical questions would advance the PBL science described above pertaining to surface interactions specifically with satellite-based observations of T and q profiles and PBL height. These questions would be answered jointly using PBL retrievals of T, q, and PBLH and surface states and fluxes including, but not limited to, latent and sensible heat flux, soil moisture, surface roughness, and vegetation structure and function.

3.3 PBL Science Lessons learned from past campaigns and surface networks

Past field campaigns provided critical observations that advanced our knowledge of the PBL's interactions with the surface. For example, the First International Satellite Land Surface Climatology Project (ISLSCP) Field Experiment (FIFE; Sellers et al. 1988) pioneered simultaneous acquisition of satellite, atmospheric, and surface data to understand coupled land-atmosphere processes in a multidisciplinary multiscale framework. This framework was subsequently tested and proven in other field campaigns sampling a range of surface – boundary layer interactions from local to regional scales (e.g., Sellers et al. 1995; Avissar et al. 2002; Redelsperger et al. 2006). Similarly pioneering work in the western Pacific Ocean (TOGA-COARE; Webster and Lukas, 1992) substantially improved our understanding of air-sea interactions and tropical weather systems, providing better model parameterizations, and an improved ability to predict large scale atmospheric variability patterns (e.g. MJO). These efforts showed that data from a PBL satellite mission are much more valuable when combined with other data sources. This includes, for example, data from other orbital platforms (e.g., measuring soil moisture, surface temperature and vegetation properties); in-situ measurements; profiles from radiosondes and aircraft; meteorological stations and flux towers providing point lower boundary properties and the surface energy balance including heat fluxes; derived gridded products for PBL boundary conditions such as surface fluxes (e.g., Miralles et al. 2025; Nelson et al. 2024); and the application of atmospheric analyses using numerical models to assimilate satellite PBL measurements. Data synthesis and fusion greatly extends the utility of the individual products (Kabat et al. 2004). In this case, global data from a PBL measuring mission would serve as the core of an array of datasets and information for improving PBL science.

NASA and the international community have conducted numerous field campaigns with a focus not only on science, but also for advancing technologies within the scientific context to better evaluate the strengths and weaknesses of different approaches in their ability to meet targeted science objectives and tailor technologies for future missions. Although some previous missions have deployed active and passive sounders for exploitation of joint retrievals, there is an even richer dataset exploiting the use of surface observations, in-situ, dropsonde and radiosonde soundings to provide insight on the challenging nature of PBL dynamics across all geographic regions and atmospheric conditions. Campaigns such as DISCOVER-AQ, ARCSIX, NAMES, and CPEX produced great examples of

datasets that can be exploited to better quantify the nature of the PBL using sounders, in-situ, and dropsonde data from urban, Arctic, and cool and warm marine environments, respectively. These data are critical for providing canonical cases for the evaluation of emerging technologies through the development of instrument forward models. Instrument demonstration and synergy campaigns also serve a unique purpose of informing the potential for multi-instrument retrievals, as exemplified by the WH²yMSIE campaign. The WH²yMSIE aircraft campaign took place between October-November 2024 and is in the process of providing additional insights about the role of the surface in the PBL and demonstrating new ways to incorporate surface information to improve PBL thermodynamic and PBLH retrieval. This campaign used simultaneous infrared and microwave observations as well as differential absorption and backscatter lidar aircraft measurements, along with surface measurements. Processing and analysis of these measurements is ongoing.

Analogous lessons learned from satellite missions pertaining to the PBL are limited because observing atmospheric properties nearer to the surface is challenging (e.g., Santanello and Schaefer, 2017). Many previous satellite-based PBL studies combined satellites (AIRS, GPS RO) and process modeling via data assimilation (e.g., Ding et al., 2021). However, despite the known limitations, it is recommended that additional investigations utilizing existing spaceborne, sub-orbital, and surface PoR be carried out to both empirically study the impacts of surface properties and heterogeneity on PBL retrieval uncertainties and improvements that can be gained by inclusion of additional surface information (e.g., Table 1).

4. PBL Technology: Thematic and data integration

The PBL surface interactions working group identified two main considerations for PBL technological development: (1) *How can we use surface information to improve T, q, and PBLH retrievals?* and (2) *What data needs do we have for addressing PBL science related to surface-atmosphere interactions?*

4.1 Improving T, q, and PBLH retrievals with surface information

4.1.1 PBL Radiative Transfer Algorithm Gaps

Radiative transfer algorithms are at the core of inverse methods for retrieving thermodynamic variables in the PBL, whether this concerns rigorous physical retrievals, or statistical AI/ML-based approaches. In the former case they are needed as forward operators, and in the latter as simulators to produce synthetic training data. As an example, the standard model for both of these approaches at the Climate and Radiation Laboratory at NASA Goddard Space Flight Center is the Community Radiative Transfer Model (CRTM; see Johnson et al., 2023 and Stegmann et al., 2025).

Radiative transfer and algorithms to retrieve T, q, and PBLH, especially in microwave frequencies, use simple assumptions and parameterizations of the surface. Accurate radiative transfer modeling in the microwave window region between the frequencies of 125 and 175 GHz is critical for thermodynamic retrievals in the PBL, particularly since photonics technology has recently enabled high-resolution observations in this frequency band. However, since this frequency range is relatively transparent and the surface emits radiation at these spectra related to moisture, it can be shown these spectra are highly sensitive to uncertainties in modeling microwave surface emission. Radiative transfer algorithms

require more advanced consideration of surface properties, given that they often assume uniform vegetation or moisture conditions despite heterogeneity of these properties. Additionally, representativeness errors are introduced to retrievals when operating over ocean since the marine PBL height is usually well below the dense averaging kernels of these retrievals (1.5-2 km?). Over tropical subtropical oceans for example, the surface-based mixed layer height is typically 200-900 m according to radiosondes. As such, current space-based retrievals of PBL thermodynamics and height are not representative of (and thus have errors related to) the surface layer, and thus cannot be used with confidence for air-sea flux retrievals or marine PBL characterization. Similarly for rainfall estimates, NASA GPM DPR (dual-precipitation radar) cannot observe rainfall below 1-2.5 km altitude over ocean due to sidelobe clutter that is related to and depends on the orientation or location of the data pixel across the radar swath. This height limitation of the lowest-clutter free bin excludes from the record rain falling from prevalent trade wind cumulus clouds rooted within the shallow marine PBL or remain below the Hadley cell subsidence inversion. Though not the strongest rain producers, these clouds have immense radiative feedbacks to the atmosphere and interact strongly with the PBL.

In the example of CRTM, surface input properties are, for ocean, sea surface temperature (SST), salinity, and wind speed and direction (translating into wave roughness spectra) as well as, for land, soil type (various kinds of sand, clay, loam, glacial ice, or farmland) and vegetation type (various kinds of forest, savanna, tundra, or bare soil). The categories of these land based inputs are adopted from the NCEP Global Forecast System (GFS) classification.

As such, key variables to consider that could be sources of error as well as, if integrated into the algorithm, improve the retrieval of T, q, and PBLH include surface emissivity (IR and microwave frequencies), land cover type, roughness, fluxes, moisture, and vegetation structure and function. There exist satellite and network-based measurements of these properties that may be viably integrated into these algorithms. Additionally, direct observations of key thermodynamic variables like q from lidar can be used as a direct constraint on microwave radiances to improve accuracy of q retrievals and increase accuracy and vertical resolution of T from microwave observations.

4.1.2 Improving PBL Retrievals using Surface Information

The PBL surface interactions working group proposes the improvement of T, q, and PBLH retrievals of the PBL mission using:

- (1) direct integration of surface property observations from the program of record into the retrieval algorithms;
- (2) post-hoc improvement of T, q, and PBLH estimates within data assimilation frameworks to produce a best estimate of T/q/PBLH; and
- (3) machine learning by integrating PBL mission spectral measurements and surface properties from the program of record as inputs to constrain T/q/PBLH.

Table 1 Ancillary Variables for Retrievals table. Method of integration refers to the number of the corresponding method type at the beginning of section 4.1.2. Variables here are for optimum improvement of q and T profiles and PBLH retrievals and data assimilation states. These are only for higher accuracy PBL information and can be mostly accomplished with PoR, and the mission is meant to stand alone without these considerations.

Geophysical Variable	Method of Integration	Potential PoR Sources
Surface emissivity	1	Landsat, EMIT, SMAP, NISAR, VIIRS
Surface type / landcover	1, 3	EMIT, Landsat, VIIRS
Roughness / roughness length	1,3	ICESat-2, GEDI, NISAR, SWOT
Vegetation structure and function	1,3	STV, GEDI, NISAR, OCO 2 & 3; PACE, VIIRS, AVHRR
Water and Energy Fluxes	2,3	ECOSTRESS, MODIS, VIIRS, flux tower networks (e.g. AmeriFlux/Fluxnet, NEON, ICOS)
Soil moisture	1,2,3	SMAP, AMSR-2, MWI
Surface / vegetation moisture	1, 2	SMAP, SWOT, NISAR, surface networks, AVHRR
Water type	1	PACE OCI
Water temperature	1,2,3	AMSR2, GMI
Ocean wind speed	1,2,3	Windsat, AMSR-2, MWI
Ocean wind direction	1,2,3	Windsat, AMSR-2, MWI
Ocean salinity	1,3	SMAP
Ice temperature	1	VIIRS
Ice Thickness	1	Cryosat2 altimeter
Ice Density	1	Cryosat2, SMAP
Ice Roughness	1,3	Cryosat2
Snow type (wet/dry)	1,2,3	MWI
Snow temperature	1,2,3	VIIRS
Snow depth	1,2,3	VIIRS
Snow density	1,3	AMSR2, MWI
Snow grain size	1,3	VIIRS

4.1.2a Direct Integration of Surface POR Measurements into PBL Retrieval Algorithms

Regarding critical surface variables to interpret PBL information, latent and sensible heat fluxes influence PBL vertical profiles but are also challenging to remotely characterize. However, there is

now a rich legacy of this data in the existing PoR (Table 1). The challenge is that much of this information is based on higher-level derived products (with their own uncertainties which may also have inconsistent assumptions with the models using these data) from what is directly observed (e.g. radiance measurements) and meteorological inputs. For example, evapotranspiration retrievals from space currently require process modeling using satellite retrievals of soil moisture, land surface temperature and other auxiliary inputs (radiation) and require rigorous assessment against observations (e.g. Volk et al. 2024). Despite these challenges, these products represent the current state-of-the-art and we propose the use of surface information from the PoR with measurements from a PBL mission and other satellites to improve the retrieval process. This allows us to bring together the full breadth of heterogeneous datasets and demonstrate new capabilities with existing measurements from the ground, sub-orbital, and space. PoR measurements of interest that can directly improve retrievals of T profile, q profile, and PBLH include, but are not necessarily limited to, those provided in Table 1 below. In addition to the data listed in Table 1, we also recommend exploration of commercially available observations (such as from the NASA commercial smallsat data acquisition (CSDA) program) that could provide additional context for retrievals and/or fill observational gaps in time and space, particularly for discrete activities focused on the training of machine learning approaches or evaluating PBL retrievals in the context of heterogeneous environments.

4.1.2b Improving the representation of PBL structure with Data Assimilation

Data assimilation frameworks constrain land surface models coupled to the atmosphere. Such frameworks can be valuable for integrating both surface information and remote sensing measurements of the atmosphere (from the PBL mission) to improve T and q profiles analyses and forecasts as well as boundary layer height. For climatological scales, the primary impact of observations is felt in how they improve representation of physical processes, for example via parameter estimation (e.g. Dagon et al. 2020, Elsaesser et al. 2025).

There are several challenging aspects for assimilating surface-related observations in both atmosphere and coupled systems, and existing (new) data assimilation capabilities need to be enhanced (already developed) to tailor to PBL unique features. The objectives are to ready data assimilation algorithms for using new observations from PBL missions while conducting Observing System Simulation Experiments (OSSEs) to evaluate the potential impact of observations from these missions. OSSEs can quantify *information gain* in terms of how observations improve or reduce uncertainty in forecasts or climate projections, providing an objective metric for the value of competing observing platforms. Challenges include:

- As the projection of observation information onto state variables depends on the background error covariance (BEC), accurately representing BEC in various scenarios and stability conditions are essential to capture the gradients at the PBL top and PBL structure (Fowler et al. 2012, Zhu et al. 2025). More studies are required with increased global data coverage, diurnal cycle representation, and high spatial resolutions to address this aspect for complicated surface processes.

- The uncertainties of radiative transfer models including surface emissivity and surface properties are also important factors that affect the assimilation of surface-sensitive radiances and their impacts on representing PBL structure. Efforts have been made to explore deriving/using better surface emissivity in data assimilation systems (e.g. Zhu et al. 2021, Karpowicz et al. 2022). Data assimilation and weather forecasts will also benefit from increased global data coverage and high spectral and spatial resolutions of new observations from PBL missions for improved surface characteristics.
- Cloud effects. All-sky microwave radiance assimilation has become common in major NWP centers and research organizations in the past decade (e.g. Geer et al. 2010, Zhu et al. 2016). Expansion of all-sky radiance assimilation to new channels and hyperspectral microwave from PBL missions would be expected. In addition, the all-sky IR radiance assimilation to increase observations used in the lower troposphere and to improve forecasts of hazardous weather events is currently being explored.
- Weakly/strongly coupled systems can be valuable for integrating both surface information and remote sensing measurements of the atmosphere from PBL missions to produce consistent state analyses and forecasts across all components. Due to different temporal/spatial scales of different components in strongly coupled systems, how to properly use observations that are involved in more than one component is worth investigating.
- Analyses generated from data assimilation systems provide better state structures for atmosphere and/or land, ocean, and the resultant analysis increments are fed back to forecast models to improve subsequent weather predictions. However, model physics tend to return to their original mechanisms within one day in the lower troposphere (including PBL) (Zhu et al. 2022). Methods for feeding back analysis increments to forecast models and retraining observation information in the PBL need to be explored.

There are also data assimilation frameworks that focus on the land surface, which can better estimate surface properties with PBL measurement inputs. For example, Ahmad et al. (2022) shows that assimilation of LAI and soil moisture permit an offline Noah-MP LSM to resolve flash drought development more quickly. Lahmers et al. (2023) shows that surface multi-variate data assimilation (including SWE, soil moisture, and LAI) are needed to capture the progression of the 2019 Mississippi basin floods over mid-west states. However, both of these studies use an offline LSM that is not coupled to the atmosphere. More recently, Y. Zhang et al. (2025) used a coupled LSM-atmosphere data assimilation framework to ingest PBL depth observations obtained using differential reflectivity (Z_{DR}) from the dual-polarization NEXRAD radar network, resulting in significantly improved rainfall forecast performance when simulating a torrential rainfall and flooding event in Kentucky. These results demonstrate the potential for PBL depth observations, especially those assimilated through coupled LSM-atmosphere frameworks, to improve NWP forecasts of impactful events.

4.1.2c Estimating PBL Variables with Data Fusion

Machine learning frameworks can similarly be used to estimate T, q, and PBLH by ingesting both spaceborne PBL measurements and surface information from the POR, or leveraging sub-orbital data (e.g. Christopoulos et al., 2025). Machine learning (ML) provides a practical pathway to robust PBLH

estimation by fusing multi-source remote sensing. Across ML methods, including gradient-boosted trees, random forests, clustering, AdaBoost, and deep neural networks, performance consistently exceeds traditional remote sensing and statistical methods (Rieutord et al., 2021; de Arruda Moreira et al., 2022; Sleeman et al., 2020). An example is the random forest approach that augments Doppler lidar estimates with meteorological data, yielding substantially lower errors and higher radiosonde agreement than lidar-only baselines (Krishnamurthy et al., 2021). Moreover, Su and Zhang (2024) trained a multi-structure deep neural network on decades of radiosonde and lidar data, using standard meteorological inputs to generate a long-term PBLH record that transfers well across climates and terrains. Furthermore, a “best-estimate” framework fused different PBLH remote-sensing products from the Department of Energy's Atmospheric Radiation Measurement (ARM) program with RF and LightGBM, which maximizes agreement with radiosondes (D. Zhang et al. 2025). ML has also enabled PBLH retrievals from AERI (Ye et al., 2021) and HyMPI (MacKinnon et al. 2023), leveraged aerosol-profile structure in complex conditions (H. Li et al., 2023), and boosted spaceborne-lidar skill via convolutional neural networks (CNNs) and denoising for low-SNR scenes (Palm et al., 2021; Selmer et al., 2024). Similarly, hyperspectral microwave and backscatter lidar (passive + active) are proposed to retrieve T , q , and PBLH as demonstrated in Gambacorta et al., 2025a; Kotsakis et al., 2023. Extending further, utilization of humidity profiles from DIAL (Carroll et al., 2022) can directly constrain water vapor radiances for IR and MW to improve accuracy of T and q but also increase the vertical resolution of both geophysical products (Turner and Lohnert 2021).

4.2 Understanding surface data needs for PBL Science

The PBL mission and specifically observations of the T and q thermodynamic profiles and PBLH have the potential to substantially advance PBL science related to surface interactions (see PBL science and applications sections 3 and 5, respectively). Here, we discuss the observational requirements for addressing PBL science and applications pertaining to surface interactions. Specifically, what spatial resolution is necessary for T , q , and PBLH, and how much uncertainty is permissible? Where, and how often, must these variables be sampled? And what additional information must be provided about other variables (from, e.g., models or PoR), both to optimize retrievals of T , q , and PBLH and provide essential environmental context for surface-relevant PBL science and applications? What gaps remain based on the wider use of PoR? How do we use retrievals of T , q , and PBLH to conduct detailed surface-to-atmosphere coupled analysis studies on PBL properties, processes, and feedbacks? To address these questions and provide guidance on requirements for a global PBL Mission, we provide a Science and Applications Traceability Matrix (SATM) that summarizes the sampling and ancillary data needs associated with each of the science questions outlined in Section 3.2 (Appendix A).

For example, studies investigating surface-atmosphere coupling strength and its influence on the PBL typically require higher-resolution observations, as do studies investigating the role of surface heterogeneity in PBL structure and evolution. Horizontal and vertical resolutions on the order of $\lesssim 3$ km and $\lesssim 300$ m, respectively, for T and q are necessary to effectively sample clear sky regions and capture transitions associated with mesoscale phenomena (e.g. thunderstorms) to evaluate and improve weather forecasting models. Similarly, finer vertical resolution would allow for improved characterization of the temperature and water vapor structure, including discriminating sharp adiabatic

gradients near the surface in shallow boundary layer conditions. At the same time, there is a fundamental difference between coupled and (partially or fully) decoupled PBLs. The coupling strength depends on the lapse rate and surface sensible heat fluxes. Measuring this coupling strength requires a fine vertical resolution, as the near-surface stable layer can be quite shallow, requiring <300 m uncertainty in PBLH. The organization of thunderstorms (including tornadic storms and mesoscale convective systems) depends on the surface coupling strength. The coupling strength also impacts near-surface air pollution, turbulence, and wind speed and has implications for air quality, wind power generation, etc (see Section 5).

Another notable science utilization of air temperature and humidity is their joint use in the computation of vapor pressure deficit (VPD) used in studying the often dominant effects of VPD on water and carbon fluxes. In fact, a recent debate has emerged about whether soil moisture or VPD limits plant functioning more (Green 2024). VPD's use in such a way requires sufficient accuracy of air temperature and humidity observations nearer to the surface where VPD impacts evaporation and leaf-level stomatal functioning more. Resolution requirements are at approximately daily and also <10km to evaluate daily scale functioning along with passive microwave soil moisture retrievals. Former studies were limited by use of AIRS which notably was unable to resolve near surface VPD sufficiently for this science study.

Additional PoR required for these studies include information on surface roughness (weekly to monthly), cover type and dynamics (weekly), soil moisture (daily), albedo (~daily), net radiation (subdaily), latent and sensible heat fluxes (subdaily), LST and sea surface temperatures (subdaily), cloud cover (subdaily), and winds (subdaily). Adding information about the vertical velocity/updrafts at the same time and vertical resolutions could lead to the estimation of vertical turbulent fluxes/eddies making it easier to identify the PBL top. Also, ML approaches to estimate PBLH rely mostly on surface sensible heat flux, land fraction, surface net solar radiation (Ayazpour et al., 2023).

Hourly resolution for Planetary Boundary Layer (PBL) height information is needed to enable the analysis of diurnal cycles and PBL height growth rates. Understanding drivers of these growth rates over land, ice, and water is critical for understanding a host of processes, including shallow to deep convection, the marine boundary layer and cloud forecasts, weather and fire weather forecasting, and science and applications that require detailed knowledge of the water cycle and weather conditions at a subdaily timescale (e.g. energy production, agriculture; Section 5). Additional PoR (see Appendix A for a full list) needed to pair with subdaily PBL thermodynamic and PBLH estimates include infrared and microwave emissivity which can be impacted by diurnal processes and states (e.g. dew on leaves).

The requirements presented in Appendix A provide guidance on the technological capabilities and observational improvements necessary for a future PBL Mission that would substantially improve a host of critical surface interactions science and applications (see Section 5). We note that the ranges in spatiotemporal and vertical resolutions presented are meant to acknowledge that requirements depend on specific applications and science goals, and, at times, are themselves uncertain. Nevertheless, they reflect values that, if achieved by the mission, can substantially advance a range of science questions

(as presented in Section 3). However, not achieving these specifications will only mean a reduced capacity of the science capability. For example, if the finest resolution requirements cannot be met, a future mission may not fully meet weather forecasting needs, particularly in challenging, heterogeneous environments or locations at the boundaries of different regimes (e.g. drylines, coastal) where finer resolution is necessary to resolve sharp changes in vertical structures. For example, fine horizontal and vertical resolutions (<3km, <300m) and low uncertainties in PBLH (e.g. 100m) are necessary for a host of disaster and risk analyses associated with food security and impacts of lives and livelihoods, where more coarse information impacts the precision of risk forecasts and the ability to adapt and mitigate impacts to infrastructure and food and fiber production. Reduced diurnal resolution would significantly impact weather and convection forecasts over land and water, and reduce the efficacy of water and resource management in drought-prone regions that respond strongly to synoptic conditions. We also note that given the different requirements across science and applications, an approach that can leverage direct adaptive resolution capabilities (i.e. providing higher resolutions in complex regimes) and/or can leverage new machine learning and data fusion approaches, as well as statistical sampling could also be a method to create higher resolution retrievals. We would recommend exploration into methods that could provide higher resolution for specific applications while also balancing costs and capabilities of a future PBL Mission.

5. PBL Applications: Science Community Co-Development and Decision Making Support

The PBL surface interactions working group identified several paths to tie PBL mission measurements to improving practitioner decision making frameworks. NASA's Earth Science to Action Strategy and Earth Action programs include both priorities of generating datasets that can be useful for decision makers as well as working directly with decision makers and integrating these datasets into their frameworks (St. Germain et al., 2024). The PBL mission's targets of T, q, and PBLH retrievals are fundamental to many land and atmospheric processes and thus have high potential to improve decision making frameworks in collaboration with practitioners.

Organizations such as NASA's Short-Term Prediction Research Transition (SPoRT) Center work with these potential stakeholders – in the early stages – to understand their challenges and develop innovative ways to use new technology, research, and advanced modeling capabilities. It is crucial to work with stakeholders at the community level, within private industry, and at state/federal government agencies prior to the development of a PBL mission. This reduces the learning curve and leads to further adoption of any decision support tools regarding applications to the cloudy and cloudless PBL. Applications that PBL measurements, along with surface measurements, can directly influence include, but are not limited to, the following:

Disaster monitoring and forecasting

Hydrologic extremes leading to disasters such as floods and droughts are connected to the PBL evolution and surface-atmosphere fluxes. Ocean-atmosphere fluxes are critically important in driving tropical cyclone intensity. For example, near-surface winds of tropical cyclones (TC) pre- and post-landfall are modulated by TC boundary layers, whose evolution on land has so far been poorly documented. Further, observational and modeling studies have shown the sensitivity of post-landfall

TC strength, re-intensification, and enhanced potential for flooding to soil moisture and PBL evolution as well as advection of surface variables from over the ocean. Decision-makers at the federal (NOAA, FEMA), state, and local level need improved forecasts that integrate high resolution PBL observations to improve disaster response to extreme hydrologic events from hurricane flooding and storm surge.

Extreme Precipitation and Landslide Risk

Atmospheric rivers (ARs) are a critical component of Western U.S. water resources planning as they supply most of the region's annual precipitation, but also pose threats of flooding, landslides, and infrastructure losses. As ARs travel over the ocean, the strong surface moisture and heat fluxes can substantially deepen the PBL, which in turn enhance ARs' ability to transport water vapor and intensify. Improving representation of ocean-atmosphere fluxes will improve coupled models' ability to forecast events. Modeling and forecasting extreme precipitation and the response of the land surface for hazardous events is important to federal agencies – such as NOAA, FEMA, DOT – as well as state and local emergency management and transportation agencies, enabling them to provide public warnings and respond with relief efforts.

Water Resource Management

PBL measurements will improve water resources monitoring pertaining to lakes, rivers, and snowmelt used in models that decision makers use at state, local governments and within private industry. Monitoring lake evaporation plays an important role in reservoir management in the Western US. Estimation of reservoir evaporation using methods such as the Penman-Monteith equation is subject to large errors owing to a lack of observations of q and to a lesser extent T above water bodies. The retrieval of q can be directly used in the Penman equation to calculate water vapor deficit or be assimilated into the PBL scheme of NWP models such as WRF-Lake. Modeling snowpack in the intermountain west is hindered by the unknown magnitude of snowmelt and sublimation that are closely dependent on PBL structure, including PBLH and profile of T and q . Availability of retrievals of T and q variables at high spatial resolution will contribute to the prediction of both seasonal and ephemeral snowpack.

Drought, Extreme Heat, and Improving Public Health

Capturing fine-scale processes in the PBL where the transfer of heat and moisture lead to extreme drought or precipitation is important for the impact of the environment on human health. The sensitivity of droughts to land-atmosphere coupling strength has been identified as key to the evolution and propagation of heatwaves and flash drought events. Public health agencies and non-governmental agencies rely on long-term records of temperature and moisture to understand and predict heat stress, vector-borne disease and infectious disease on sub-seasonal to seasonal scales. A better understanding of both dry and wet hydrologic extremes through surface and PBL observations will yield societal and economic benefits.

Agriculture: Croplands and Rangelands

Crop and rangeland forage predictive models require modeling of evaporation with PBL mission measurements (T and q profiles) particularly useful for providing information about vapor pressure

deficit that directly influences plant functioning. Air temperatures are also useful for predicting crop phenology. Therefore, both T and q profiles input or assimilated within crop models can improve both crop and grass forage phenological monitoring and crop and forage yield prediction. Improving modeling of land surface interactions and that drive extreme drought are important for providing specialized forecasts for crop yield and supply chain fluctuations.

Wildfire Risk, Forecasting, and Mitigation

The boundary layer and surface conditions favoring wildfire and rapid growth are well understood, but there remain significant gaps in the continuous measurement of the land surface and boundary layer interactions. Improved observations of the land surface-atmosphere interactions for T, q, PBLH, with lightning, will advance coupled atmosphere-fire behavior models developed by the public and private sector and used by Federal, State, and Local agencies.

Air Quality and Greenhouse Gas Monitoring and Forecasting

Poor air quality degrades visibility, threatens human health, and perturbs ecosystem functioning. Aerosols, a group of regulated air pollutants, can significantly impact surface fluxes, temperature, humidity and the PBL height, which feed back to air quality (i.e., lower PBL height can lead to poorer air quality). More accurate PBL and land surface measurements can be leveraged by federal, state, and local air quality agencies to improve air quality alert lead times and private sector environmental firms will be able to improve modeling and prediction of air pollution levels. Accurately measured PBL structural information will also benefit the attribution of air pollutants to local and nonlocal sources. The source attribution information is valuable for evaluating and refining bottom-up emission inventories and mitigation strategies developed by federal, state, and local environmental and air quality agencies.

Energy Infrastructure Security and Grid Resilience

The energy sector relies heavily on observations and forecasts for the lower atmosphere for wind, T, q, and trace gases, as well as rivers and reservoirs, and land surface. Key applications include surface & PBL temperature, wind, turbulence, and stability for power load forecasting (coal-fire, nuclear, wind energy, and solar); leak detection and monitoring of concentration of methane and other gases; and safety and dispersion analysis of leaked gases, emissions, and harmful pollutants.

National Defense

Coupled land-atmosphere models with improved PBL observations can aid national defense applications and decisions by the DoD and National Guard. Knowledge of how the land surface impacts environmental hazards such as dust storms, flooding, wildfires, and extreme heat are important for asset placement, movement, protection, and scenario planning.

Appendix A. Science and Applications Traceability Matrix (SATM) focused on the spatial and temporal sampling needs for surface interactions and processes.

Geophysical Variables and Measurement Requirements	Potential Measurement Technologies																		
<p><u>Direct PBL observational requirements:</u> Spatial distributions of T and q thermodynamic profiles in clear and cloudy conditions</p> <ul style="list-style-type: none"> ● Vertical resolution: 100m - 300m (Q1+Q3) <ul style="list-style-type: none"> ○ To capture local and sharp adiabatic gradients and inversion layers; calculate PBL depth ● Horizontal resolution: 3km (Q1+Q2), 20km (Q3) <ul style="list-style-type: none"> ○ Finer resolution needed over transition areas, and for mesoscale meteorology, coarser resolution sufficient for diurnal processes and PBL evolution ● Uncertainty: $\leq 1\text{ K}$, $\leq 1\text{g/m}^3$ <p>PBL Height</p> <ul style="list-style-type: none"> ● Horizontal resolution: 3km (Q2), 20km (Q1+Q3) ● Uncertainty: 100-300m <ul style="list-style-type: none"> ○ Constraint on PBL depth <p>Temporal sampling (Q1-Q3):</p> <ul style="list-style-type: none"> ● Multiple times per day at the same location, including midday to capture PBL depth; higher resolution diurnal sampling needed for improved process studies <hr/> <p><u>Coincident measurement requirements (not delivered by the PBL mission) with known sources in the PoR:</u></p> <p>Surface type and dynamics:</p> <table border="0"> <tr> <td>● LST</td> <td>● Topography</td> </tr> <tr> <td>● Cover type / land cover and change</td> <td>● Ice properties</td> </tr> <tr> <td>● Leaf area index & phenology</td> <td>● Snow properties</td> </tr> <tr> <td>● Soil and vegetation moisture</td> <td>● Wave properties</td> </tr> <tr> <td>● 3D vegetation structure</td> <td>● Water properties</td> </tr> <tr> <td>● Surface roughness</td> <td></td> </tr> </table> <p>Surface-atmosphere interactions:</p> <table border="0"> <tr> <td>● Latent and sensible heat flux</td> <td>● Salinity</td> </tr> <tr> <td>● Albedo</td> <td>● Winds</td> </tr> <tr> <td>● Downwelling & net radiation</td> <td>● Sea surface temperature</td> </tr> </table>	● LST	● Topography	● Cover type / land cover and change	● Ice properties	● Leaf area index & phenology	● Snow properties	● Soil and vegetation moisture	● Wave properties	● 3D vegetation structure	● Water properties	● Surface roughness		● Latent and sensible heat flux	● Salinity	● Albedo	● Winds	● Downwelling & net radiation	● Sea surface temperature	<p><u>Direct PBL observation technologies:</u> Clear and partial cloudy (with COD < 1)</p> <ul style="list-style-type: none"> ● IR sounding ● Shortwave multi-angle ● Tomography ● Lidar (DIAL, BSL) <p>Clear and cloudy conditions</p> <ul style="list-style-type: none"> ● MW sounding ● GNSS-RO ● Radar (DAR) <p>Temporal sampling approaches</p> <ul style="list-style-type: none"> ● LEO inclined orbit (IR + MW sounders, Lidar) ● GEO (IR sounder) ● Cubesat constellation (delta T) ● Suborbital (DIAL, DAR, Doppler lidar) <hr/> <p><u>PoR sources for ancillary variables:</u> Surface type and dynamics:</p> <ul style="list-style-type: none"> ● Spaceborne: GEO (VIS/IR/TIR), LEO (VIS/IR/TIR, passive/active MW, Lidar) ● Sub-orbital: Passive MSI/HSI, TIR, MW; Active Lidar, MW ● Surface networks: flux networks (e.g. Ameriflux/Fluxnet, ICOS, NEON) mesonets, atmospheric observatories (e.g. DOE ARM), soil moisture networks (USCRN, SCAN, ISMN) <p>Surface-atmosphere interactions:</p> <ul style="list-style-type: none"> ● Spaceborne: GEO (VIS/IR/TIR), LEO (VIS/IR/TIR, passive/active MW) ● Sub-orbital: Passive MSI/HSI, TIR, active and passive MW ● Surface networks: flux networks, mesonets, radiation networks (e.g. RadCalNet), atmospheric observatories, soundings, profiling networks (e.g. MPLNET), soil moisture networks
● LST	● Topography																		
● Cover type / land cover and change	● Ice properties																		
● Leaf area index & phenology	● Snow properties																		
● Soil and vegetation moisture	● Wave properties																		
● 3D vegetation structure	● Water properties																		
● Surface roughness																			
● Latent and sensible heat flux	● Salinity																		
● Albedo	● Winds																		
● Downwelling & net radiation	● Sea surface temperature																		
<p>GEO - Geostationary HSI - Hyperspectral imaging IR - Infrared LEO - Low Earth orbit</p>	<p>MSI - Multispectral imaging MW - Microwave TIR - Thermal infrared</p>																		

References

- Ahmad, S. K., Kumar, S. V., Lahmers, T. M., Wang, S., Liu, P., Wrzesien, M. L., et al. (2022). Flash Drought Onset and Development Mechanisms Captured With Soil Moisture and Vegetation Data Assimilation. *Water Resources Research*, 58(12), e2022WR032894. <https://doi.org/10.1029/2022WR032894>
- Avissar, R., Silva Dias, P. L., Silva Dias, M. A. F., & Nobre, C. (2002). The Large-Scale Biosphere-Atmosphere Experiment in Amazonia (LBA): Insights and future research needs. *Journal of Geophysical Research: Atmospheres*, 107(D20). <https://doi.org/10.1029/2002JD002704>
- Avşar, E. (2018). *Benefits to the Environment and Society from the Availability and Use of AMDAR Data* (WIGOS Technical Report No. 2018– 01). Geneva: World Meteorological Organization. Retrieved from <http://rgdoi.net/10.13140/RG.2.2.30903.16806>
- Ayazpour, Z., Tao, S., Li, D., Scarino, A. J., Kuehn, R. E., & Sun, K. (2023). Estimates of the spatially complete, observational-data-driven planetary boundary layer height over the contiguous United States. *Atmospheric Measurement Techniques*, 16(2), 563–580. <https://doi.org/10.5194/amt-16-563-2023>
- Baldrige, A. M., Hook, S. J., Grove, C. I., & Rivera, G. (2009). The ASTER spectral library version 2.0. *Remote Sensing of Environment*, 113(4), 711–715. <https://doi.org/10.1016/j.rse.2008.11.007>
- Campbell, M. A., Ferguson, C. R., Burrows, D. A., Beauharnois, M., Xia, G., & Bosart, L. F. (2019). Diurnal Effects of Regional Soil Moisture Anomalies on the Great Plains Low-Level Jet. *Monthly Weather Review*, 147(12), 4611–4631. <https://doi.org/10.1175/MWR-D-19-0135.1>
- Carroll, B. J., Nehrir, A. R., Kooi, S. A., Collins, J. E., Barton-Grimley, R. A., Notari, A., et al. (2022). Differential absorption lidar measurements of water vapor by the High Altitude Lidar Observatory (HALO): retrieval framework and first results. *Atmospheric Measurement Techniques*, 15(3), 605–626. <https://doi.org/10.5194/amt-15-605-2022>
- Christopoulos, J. A., Saide, P. E., Ferrare, R., Collister, B., Barton-Grimley, R. A., Scarino, A. J., et al. (2025). Improving Planetary Boundary Layer Height Estimation From Airborne Lidar Instruments. *Journal of Geophysical Research: Atmospheres*, 130(9), e2024JD042538. <https://doi.org/10.1029/2024JD042538>
- Dagon, K., Sanderson, B. M., Fisher, R. A., & Lawrence, D. M. (2020). A machine learning approach to emulation and biophysical parameter estimation with the Community Land Model, version 5. *Advances in Statistical Climatology, Meteorology and Oceanography*, 6(2), 223–244. <https://doi.org/10.5194/ascmo-6-223-2020>
- de Arruda Moreira, G., Sánchez-Hernández, G., Guerrero-Rascado, J. L., Cazorla, A., & Alados-Arboledas, L. (2022). Estimating the urban atmospheric boundary layer height from remote sensing applying machine learning techniques. *Atmospheric Research*, 266, 105962. <https://doi.org/10.1016/j.atmosres.2021.105962>
- Ding, F., Iredell, L., Theobald, M., Wei, J., & Meyer, D. (2021). PBL Height From AIRS, GPS RO, and MERRA-2 Products in NASA GES DISC and Their 10-Year Seasonal Mean Intercomparison. *Earth and Space Science*, 8(9), e2021EA001859. <https://doi.org/10.1029/2021EA001859>

- Eder, F., Schmidt, M., Damian, T., Träumner, K., & Mauder, M. (2015). Mesoscale Eddies Affect Near-Surface Turbulent Exchange: Evidence from Lidar and Tower Measurements. *Journal of Applied Meteorology and Climatology*, 54(1), 189–206. <https://doi.org/10.1175/JAMC-D-14-0140.1>
- Elsaesser, G. S., van Lier-Walqui, M., Yang, Q., Kelley, M., Ackerman, A. S., Fridlind, A. M., et al. (2025). Using Machine Learning to Generate a GISS ModelE Calibrated Physics Ensemble (CPE). *Journal of Advances in Modeling Earth Systems*, 17(4), e2024MS004713. <https://doi.org/10.1029/2024MS004713>
- Forster, L., Richardson, M. T., Davis, A. B., Hess-Flores, M. A., Yanovsky, I., Ryan, J., et al. (2025). Scientific applications of multi-angle measurements to reconstruct Earth's atmosphere through tomography. *Bulletin of the American Meteorological Society*, in review.
- Fowler, A., Bannister, R., & Eyre, J. (2012). A new floating model level scheme for the assimilation of boundary-layer top inversions: the univariate assimilation of temperature. *Quarterly Journal of the Royal Meteorological Society*, 138(664), 682–698. <https://doi.org/10.1002/qj.955>
- Gambacorta, A., Kotsakis, A., Kroodsmas, R., Nowotnick, E., Serbin, S., Nehrir, A., et al. (2024). The West-Coast Hyperspectral Microwave Sensor Intensive Experiment (WHYMSIE). In *IGARSS 2024 - 2024 IEEE International Geoscience and Remote Sensing Symposium* (pp. 1430–1432). Athens, Greece: IEEE. <https://doi.org/10.1109/IGARSS53475.2024.10641560>
- Gambacorta, A., Kotsakis, A., Gershman, D., Shahroudi, N., Rosenberg, R., Blaisdell, J., et al. (2025a). Improved Planetary Boundary Layer Sounding Using Hyperspectral Microwave and Backscatter Lidar Data Fusion. *IEEE Transactions on Geoscience and Remote Sensing*, *Accepted*.
- Gambacorta, A., Pradhan, O., Stephen, M., Gambini, F., Misra, S., Ogut, M., et al. (2025b). The Advanced Ultra-high Resolution Optical RAdiometer (AURORA) Pathfinder. Presented at the 15th Conference on Transition of Research To Operations, 105th American Meteorological Society Annual Meeting, New Orleans, LA. Retrieved from <https://ams.confex.com/ams/105ANNUAL/meetingapp.cgi/Paper/454398>
- Gambini, F., Moreira, R., Robles, D., Gambacorta, A., & Stephen, M. (2024). An Ultra-Compact, Narrow-Bandwidth, and High-Density Channel Photonic Integrated Channelizer Based on Serial Arrayed Waveguide Grating Architecture. *Journal of Lightwave Technology*, 42(8), 2908–2916. <https://doi.org/10.1109/JLT.2024.3349932>
- Geer, A. J., Bauer, P., & Lopez, P. (2010). Direct 4D-Var assimilation of all-sky radiances. Part II: Assessment. *Quarterly Journal of the Royal Meteorological Society*, 136(652), 1886–1905. <https://doi.org/10.1002/qj.681>
- Geerts, B., Parsons, D., Ziegler, C. L., Weckwerth, T. M., Biggerstaff, M. I., Clark, R. D., et al. (2017). The 2015 Plains Elevated Convection at Night Field Project. *Bulletin of the American Meteorological Society*, 98(4), 767–786. <https://doi.org/10.1175/BAMS-D-15-00257.1>
- Green, J. K. (2024). The intricacies of vegetation responses to changing moisture conditions. *New Phytologist*, 244(6), 2156–2162. <https://doi.org/10.1111/nph.20182>
- Green, J. K., Konings, A. G., Alemohammad, S. H., Berry, J., Entekhabi, D., Kolassa, J., et al. (2017). Regionally strong feedbacks between the atmosphere and terrestrial biosphere. *Nature Geoscience*, 10(6), 410–414. <https://doi.org/10.1038/ngeo2957>

- Helbig, M., Gerken, T., Beamesderfer, E. R., Baldocchi, D. D., Banerjee, T., Biraud, S. C., et al. (2021). Integrating continuous atmospheric boundary layer and tower-based flux measurements to advance understanding of land-atmosphere interactions. *Agricultural and Forest Meteorology*, 307, 108509. <https://doi.org/10.1016/j.agrformet.2021.108509>
- Huang, X., Chen, X., Zhou, D. K., & Liu, X. (2016). An Observationally Based Global Band-by-Band Surface Emissivity Dataset for Climate and Weather Simulations. *Journal of the Atmospheric Sciences*, 73(9), 3541–3555. <https://doi.org/10.1175/JAS-D-15-0355.1>
- Johnson, B. T., Dang, C., Stegmann, P., Liu, Q., Moradi, I., & Auligne, T. (2023). The Community Radiative Transfer Model (CRTM): Community-Focused Collaborative Model Development Accelerating Research to Operations. *Bulletin of the American Meteorological Society*, 104(10), E1817–E1830. <https://doi.org/10.1175/BAMS-D-22-0015.1>
- Kabat, P., Claussen, M., Dirmeyer, P. A., Gash, J. H. C., De Guenni, L. B., Meybeck, M., et al. (Eds.). (2004). *Vegetation, Water, Humans and the Climate: A New Perspective on an Interactive System*. Berlin, Heidelberg: Springer Berlin Heidelberg. <https://doi.org/10.1007/978-3-642-18948-7>
- Karpowicz, B. M., Zhu, Y., Munchak, S. J., & McCarty, W. (2022). Assessment of Retrieved GMI Emissivity over Land, Snow, and Sea Ice in the GEOS System. *Journal of Atmospheric and Oceanic Technology*, 39(10), 1433–1443. <https://doi.org/10.1175/JTECH-D-21-0187.1>
- Kotsakis, A., Gambacorta, A., MacKinnon, J., Piepmeier, J., Kroodsma, R., Santanello, J., et al. (2023). Hyperspectral Microwave Measurement Demonstrations of Improved Thermodynamic Sounding from Space. In *IGARSS 2023 - 2023 IEEE International Geoscience and Remote Sensing Symposium* (pp. 1448–1449). Pasadena, CA, USA: IEEE. <https://doi.org/10.1109/IGARSS52108.2023.10282289>
- Krishnamurthy, R., Newsom, R. K., Berg, L. K., Xiao, H., Ma, P.-L., & Turner, D. D. (2021). On the estimation of boundary layer heights: a machine learning approach. *Atmospheric Measurement Techniques*, 14(6), 4403–4424. <https://doi.org/10.5194/amt-14-4403-2021>
- Kuang, C., Giangrande, S., Serbin, S., Elsaesser, G., Gentine, P., Heus, T., et al. (2023). *Science Plan for the Deployment of the Third ARM Mobile Facility to the Southeastern United States at the Bankhead National Forest, Alabama (AMF3 BNF)* (No. DOE/SC-ARM--23-035, 2280575). <https://doi.org/10.2172/2280575>
- Lahmers, T. M., Kumar, S. V., Locke, K. A., Wang, S., Getirana, A., Wrzesien, M. L., et al. (2023). Interconnected hydrologic extreme drivers and impacts depicted by remote sensing data assimilation. *Scientific Reports*, 13(1), 3411. <https://doi.org/10.1038/s41598-023-30484-4>
- Lareau, N. P., Nauslar, N. J., Bentley, E., Roberts, M., Emmerson, S., Brong, B., et al. (2022). Fire-Generated Tornadoic Vortices. *Bulletin of the American Meteorological Society*, 103(5), E1296–E1320. <https://doi.org/10.1175/BAMS-D-21-0199.1>
- L’Ecuyer, T. S., Drouin, B. J., Anheuser, J., Grames, M., Henderson, D. S., Huang, X., et al. (2021). The Polar Radiant Energy in the Far Infrared Experiment: A New Perspective on Polar Longwave Energy Exchanges. *Bulletin of the American Meteorological Society*, 102(7), E1431–E1449. <https://doi.org/10.1175/BAMS-D-20-0155.1>
- Li, H., Liu, B., Ma, X., Jin, S., Wang, W., Fan, R., et al. (2023). Estimation of Planetary Boundary Layer Height From Lidar by Combining Gradient Method and Machine Learning Algorithms.

- IEEE Transactions on Geoscience and Remote Sensing*, 61, 1–11.
<https://doi.org/10.1109/TGRS.2023.3329122>
- Li, X., Ault, T., Richardson, A. D., Carrillo, C. M., Lawrence, D. M., Lombardozzi, D., et al. (2023). Impacts of shifting phenology on boundary layer dynamics in North America in the CESM. *Agricultural and Forest Meteorology*, 330, 109286.
<https://doi.org/10.1016/j.agrformet.2022.109286>
- Lin, H., Li, Y., & Zhao, L. (2022). Partitioning of Sensible and Latent Heat Fluxes in Different Vegetation Types and Their Spatiotemporal Variations Based on 203 FLUXNET Sites. *Journal of Geophysical Research: Atmospheres*, 127(21), e2022JD037142.
<https://doi.org/10.1029/2022JD037142>
- Liu, C., Fedorovich, E., Huang, J., Hu, X.-M., Wang, Y., & Lee, X. (2019). Impact of Aerosol Shortwave Radiative Heating on Entrainment in the Atmospheric Convective Boundary Layer: A Large-Eddy Simulation Study. *Journal of the Atmospheric Sciences*, 76(3), 785–799.
<https://doi.org/10.1175/JAS-D-18-0107.1>
- MacKinnon, J., Gambacorta, A., Piepmeier, J., Stephen, M., Kroodsma, R., Santanello, J., et al. (2023). Deep Neural Networks For Evaluating Future Satellite-Based Hyperspectral Microwave Sensor Designs. In *IGARSS 2023 - 2023 IEEE International Geoscience and Remote Sensing Symposium* (pp. 5210–5213). Pasadena, CA, USA: IEEE.
<https://doi.org/10.1109/IGARSS52108.2023.10282220>
- Miralles, D. G., Bonte, O., Koppa, A., Baez-Villanueva, O. M., Tronquo, E., Zhong, F., et al. (2025). GLEAM4: global land evaporation and soil moisture dataset at 0.1° resolution from 1980 to near present. *Scientific Data*, 12(1), 416. <https://doi.org/10.1038/s41597-025-04610-y>
- Molod, A., Salmun, H., & Marquardt Collow, A. B. (2019). Annual Cycle of Planetary Boundary Layer Heights Estimated From Wind Profiler Network Data. *Journal of Geophysical Research: Atmospheres*, 124(12), 6207–6221. <https://doi.org/10.1029/2018JD030102>
- National Academies of Sciences, Engineering, and Medicine. (2018). *Thriving on Our Changing Planet: A Decadal Strategy for Earth Observation from Space*. Washington, D.C.: National Academies Press. Retrieved from <https://www.nap.edu/catalog/24938>
- Nelson, J. A., Walther, S., Gans, F., Kraft, B., Weber, U., Novick, K., et al. (2024). X-BASE: the first terrestrial carbon and water flux products from an extended data-driven scaling framework, FLUXCOM-X. *Biogeosciences*, 21(22), 5079–5115. <https://doi.org/10.5194/bg-21-5079-2024>
- Nicholls, S., Gambacorta, A., Kroodsma, R., Rosenberg, R., Blaisdell, J., Stegmann, P., et al. (2025). First Light Results of the CoSMIR-H Hyperspectral Microwave Radiometer During the WH2yMSIE Field Campaign. *IEEE Geoscience and Remote Sensing Letters*, in submission
- Pal, S., Prince, N. E., Anand, M., & Hamel, M. (2025). Aerosol transport and associated boundary layer thermodynamics under contrasting synoptic conditions over a semiarid site. *Science of The Total Environment*, 962, 178357. <https://doi.org/10.1016/j.scitotenv.2024.178357>
- Paleri, S., Wanner, L., Sühring, M., Desai, A. R., Mauder, M., & Metzger, S. (2025). Impact of Surface Heterogeneity Induced Secondary Circulations on the Atmospheric Boundary Layer. *Boundary-Layer Meteorology*, 191(1), 3. <https://doi.org/10.1007/s10546-024-00893-7>

- Palm, S. P., Selmer, P., Yorks, J., Nicholls, S., & Nowottnick, E. (2021). Planetary Boundary Layer Height Estimates From ICESat-2 and CATS Backscatter Measurements. *Frontiers in Remote Sensing*, 2. <https://doi.org/10.3389/frsen.2021.716951>
- Peterson, D. A., Fromm, M. D., McRae, R. H. D., Campbell, J. R., Hyer, E. J., Taha, G., et al. (2021). Australia's Black Summer pyrocumulonimbus super outbreak reveals potential for increasingly extreme stratospheric smoke events. *Npj Climate and Atmospheric Science*, 4(1), 38. <https://doi.org/10.1038/s41612-021-00192-9>
- Redelsperger, J.-L., Thorncroft, C. D., Diedhiou, A., Lebel, T., Parker, D. J., & Polcher, J. (2006). African Monsoon Multidisciplinary Analysis: An International Research Project and Field Campaign. *Bulletin of the American Meteorological Society*, 87(12), 1739–1746. <https://doi.org/10.1175/BAMS-87-12-1739>
- Rieutord, T., Aubert, S., & Machado, T. (2021). Deriving boundary layer height from aerosol lidar using machine learning: KABL and ADABL algorithms. *Atmospheric Measurement Techniques*, 14(6), 4335–4353. <https://doi.org/10.5194/amt-14-4335-2021>
- Santanello, J. A., & Schaefer, A. J. (2017). The Importance and Current Limitations of Planetary Boundary Layer (PBL) Retrieval from Space (Vol. 97, p. 998). Presented at the 97th American Meteorological Society Annual Meeting, Seattle, WA.
- Santanello, J. A., Dirmeyer, P. A., Ferguson, C. R., Findell, K. L., Tawfik, A. B., Berg, A., et al. (2018). Land–Atmosphere Interactions: The LoCo Perspective. *Bulletin of the American Meteorological Society*, 99(6), 1253–1272. <https://doi.org/10.1175/BAMS-D-17-0001.1>
- Santanello Jr., J. A., Lawston, P., Kumar, S., & Dennis, E. (2019). Understanding the Impacts of Soil Moisture Initial Conditions on NWP in the Context of Land–Atmosphere Coupling. *Journal of Hydrometeorology*, 20(5), 793–819. <https://doi.org/10.1175/JHM-D-18-0186.1>
- Sellers, P., Hall, F., Ranson, K. J., Margolis, H., Kelly, B., Baldocchi, D., et al. (1995). The Boreal Ecosystem–Atmosphere Study (BOREAS): An Overview and Early Results from the 1994 Field Year. *Bulletin of the American Meteorological Society*, 76(9), 1549–1577. [https://doi.org/10.1175/1520-0477\(1995\)076%253C1549:TBESAO%253E2.0.CO;2](https://doi.org/10.1175/1520-0477(1995)076%253C1549:TBESAO%253E2.0.CO;2)
- Sellers, P. J., Hall, F. G., Asrar, G., Strebel, D. E., & Murphy, R. E. (1988). The First ISLSCP Field Experiment (FIFE). *Bulletin of the American Meteorological Society*, 69(1), 22–27. [https://doi.org/10.1175/1520-0477\(1988\)069%253C0022:TFIFE%253E2.0.CO;2](https://doi.org/10.1175/1520-0477(1988)069%253C0022:TFIFE%253E2.0.CO;2)
- Selmer, P., Yorks, J. E., Nowottnick, E. P., Cresanti, A., & Christian, K. E. (2024). A Deep Learning Lidar Denoising Approach for Improving Atmospheric Feature Detection. *Remote Sensing*, 16(15), 2735. <https://doi.org/10.3390/rs16152735>
- Shupe, M. D., Rex, M., Blomquist, B., Persson, P. O. G., Schmale, J., Uttal, T., et al. (2022). Overview of the MOSAiC expedition: Atmosphere. *Elem Sci Anth*, 10(1), 00060. <https://doi.org/10.1525/elementa.2021.00060>
- Simon, J. S., Bragg, A. D., Dirmeyer, P. A., & Chaney, N. W. (2021). Semi-Coupling of a Field-Scale Resolving Land-Surface Model and WRF-LES to Investigate the Influence of Land-Surface Heterogeneity on Cloud Development. *Journal of Advances in Modeling Earth Systems*, 13(10), e2021MS002602. <https://doi.org/10.1029/2021MS002602>

- Sisterson, D. L., Pepler, R. A., Cress, T. S., Lamb, P. J., & Turner, D. D. (2016). The ARM Southern Great Plains (SGP) Site. *Meteorological Monographs*, 57(1), 6.1-6.14. <https://doi.org/10.1175/AMSMONOGRAPHS-D-16-0004.1>
- Sleeman, J., Halem, M., Yang, Z., Caicedo, V., Demoz, B., & Delgado, R. (2020). A Deep Machine Learning Approach for Lidar Based Boundary Layer Height Detection. In *IGARSS 2020 - 2020 IEEE International Geoscience and Remote Sensing Symposium* (pp. 3676–3679). Waikoloa, HI, USA: IEEE. <https://doi.org/10.1109/IGARSS39084.2020.9324191>
- Sorooshian, A., Siu, L. W., Butler, K., Brunke, M. A., Cairns, B., Chellappan, S., et al. (2025). The NASA ACTIVATE Mission. *Bulletin of the American Meteorological Society*, 106(8), E1517–E1538. <https://doi.org/10.1175/BAMS-D-24-0136.1>
- Späth, F., Rajtschan, V., Weber, T. K. D., Morandage, S., Lange, D., Abbas, S. S., et al. (2023). The land–atmosphere feedback observatory: a new observational approach for characterizing land–atmosphere feedback. *Geoscientific Instrumentation, Methods and Data Systems*, 12(1), 25–44. <https://doi.org/10.5194/gi-12-25-2023>
- St. Germain, K., Robinson, J., Boukabara, S., Wagner, T., Seablom, M., Sylak-Glassman, E., et al. (2024). *Earth Science to Action Strategy 2024-2034*. National Aeronautics and Space Administration. Retrieved from https://assets.science.nasa.gov/content/dam/science/esd/earth-science-division/earth-science-to-action/ES2A_Booklet_web.pdf
- Stegmann, P., Johnson, B., Moradi, I., Karpowicz, B., McCarty, W., Liu, H., et al. (2025). The CRTM transmittance coefficient package. *Journal of Quantitative Spectroscopy and Radiative Transfer*, 336, 109380. <https://doi.org/10.1016/j.jqsrt.2025.109380>
- Su, T., & Zhang, Y. (2024). Deep-learning-derived planetary boundary layer height from conventional meteorological measurements. *Atmospheric Chemistry and Physics*, 24(11), 6477–6493. <https://doi.org/10.5194/acp-24-6477-2024>
- Su, T., Li, Z., Li, C., Li, J., Han, W., Shen, C., et al. (2020). The significant impact of aerosol vertical structure on lower atmosphere stability and its critical role in aerosol–planetary boundary layer (PBL) interactions. *Atmospheric Chemistry and Physics*, 20(6), 3713–3724. <https://doi.org/10.5194/acp-20-3713-2020>
- Sullivan, J. T., Stauffer, R. M., Thompson, A. M., Tzortziou, M. A., Loughner, C. P., Jordan, C. E., & Santanello, J. A. (2023). Surf, Turf, and Above the Earth: Unmet Needs for Coastal Air Quality Science in the Planetary Boundary Layer (PBL). *Earth's Future*, 11(6), e2023EF003535. <https://doi.org/10.1029/2023EF003535>
- Taylor, C. M., Gounou, A., Guichard, F., Harris, P. P., Ellis, R. J., Couvreux, F., & De Kauwe, M. (2011). Frequency of Sahelian storm initiation enhanced over mesoscale soil-moisture patterns. *Nature Geoscience*, 4(7), 430–433. <https://doi.org/10.1038/ngeo1173>
- Taylor, C. M., De Jeu, R. A. M., Guichard, F., Harris, P. P., & Dorigo, W. A. (2012). Afternoon rain more likely over drier soils. *Nature*, 489(7416), 423–426. <https://doi.org/10.1038/nature11377>
- Teixeira, J., Piepmeier, J. R., Nehrir, A. R., Ao, C. O., Chen, S. S., Clayson, C. A., et al. (2025). Toward a Global Planetary Boundary Layer Observing System: A Summary. *Bulletin of the American Meteorological Society*, 106(8), E1566–E1579. <https://doi.org/10.1175/BAMS-D-23-0228.1>

- Tian, J., Zhang, Y., Klein, S. A., Terai, C. R., Caldwell, P. M., Beydoun, H., et al. (2024). How Well Does the DOE Global Storm Resolving Model Simulate Clouds and Precipitation Over the Amazon? *Geophysical Research Letters*, *51*(14), e2023GL108113. <https://doi.org/10.1029/2023GL108113>
- Torres, V., Gambini, F., Mohammed, P., Robles, D., Leong, E., Coon, M., et al. (2025). Noise Figure Characterization of the Hyperspectral Microwave Photonic Instrument (HyMPI). *Photonics Technology Letters*, in press. <https://doi.org/10.1109/LPT.2025.3612866>
- Turner, D. D., & Löhnert, U. (2021). Ground-based temperature and humidity profiling: combining active and passive remote sensors. *Atmospheric Measurement Techniques*, *14*(4), 3033–3048. <https://doi.org/10.5194/amt-14-3033-2021>
- Volk, J. M., Huntington, J. L., Melton, F. S., Allen, R., Anderson, M., Fisher, J. B., et al. (2024). Assessing the accuracy of OpenET satellite-based evapotranspiration data to support water resource and land management applications. *Nature Water*, *2*(2), 193–205. <https://doi.org/10.1038/s44221-023-00181-7>
- Webster, P. J., & Lukas, R. (1992). TOGA COARE: The Coupled Ocean–Atmosphere Response Experiment. *Bulletin of the American Meteorological Society*, *73*(9), 1377–1416. [https://doi.org/10.1175/1520-0477\(1992\)073%253C1377:TCTCOR%253E2.0.CO;2](https://doi.org/10.1175/1520-0477(1992)073%253C1377:TCTCOR%253E2.0.CO;2)
- Wulfmeyer, V., Hardesty, R. M., Turner, D. D., Behrendt, A., Cadeddu, M. P., Di Girolamo, P., et al. (2015). A review of the remote sensing of lower tropospheric thermodynamic profiles and its indispensable role for the understanding and the simulation of water and energy cycles. *Reviews of Geophysics*, *53*(3), 819–895. <https://doi.org/10.1002/2014RG000476>
- Wulfmeyer, V., Turner, D. D., Baker, B., Banta, R., Behrendt, A., Bonin, T., et al. (2018). A New Research Approach for Observing and Characterizing Land–Atmosphere Feedback. *Bulletin of the American Meteorological Society*, *99*(8), 1639–1667. <https://doi.org/10.1175/BAMS-D-17-0009.1>
- Wulfmeyer, V., Späth, F., Behrendt, A., Jach, L., Warrach-Sagi, K., Ek, M., et al. (2020). The GEWEX Land–Atmosphere Feedback Observatory (GLAFO). *GEWEX Quarterly*, *30*(1), 6–11.
- Xi, X., Yang, Q., Liu, C., Shupe, M. D., Han, B., Peng, S., et al. (2024). Evaluation of the Planetary Boundary Layer Height From ERA5 Reanalysis With MOSAiC Observations Over the Arctic Ocean. *Journal of Geophysical Research: Atmospheres*, *129*(12), e2024JD040779. <https://doi.org/10.1029/2024JD040779>
- Ye, J., Liu, L., Wang, Q., Hu, S., & Li, S. (2022). A Novel Machine Learning Algorithm for Planetary Boundary Layer Height Estimation Using AERI Measurement Data. *IEEE Geoscience and Remote Sensing Letters*, *19*, 1–5. <https://doi.org/10.1109/LGRS.2021.3073048>
- Yoneyama, K., Zhang, C., & Long, C. N. (2013). Tracking Pulses of the Madden–Julian Oscillation. *Bulletin of the American Meteorological Society*, *94*(12), 1871–1891. <https://doi.org/10.1175/BAMS-D-12-00157.1>
- Zhang, D., Comstock, J., Sivaraman, C., Mo, K., Krishnamurthy, R., Tian, J., et al. (2025). Best estimate of the planetary boundary layer height from multiple remote sensing measurements. *Atmospheric Measurement Techniques*, *18*(14), 3453–3475. <https://doi.org/10.5194/amt-18-3453-2025>

- Zhang, X., Cai, C., Hu, X.-M., Gao, L., Xu, X., Hu, J., & Chen, H. (2022). Aerosols consistently suppress the convective boundary layer development. *Atmospheric Research*, 269, 106032. <https://doi.org/10.1016/j.atmosres.2022.106032>
- Zhang, Yuanjie, Li, D., Lin, Z., Santanello, J. A., & Gao, Z. (2019). Development and Evaluation of a Long-Term Data Record of Planetary Boundary Layer Profiles From Aircraft Meteorological Reports. *Journal of Geophysical Research: Atmospheres*, 124(4), 2008–2030. <https://doi.org/10.1029/2018JD029529>
- Zhang, Yunji, Stensrud, D. J., Comer, C. L., & Stouffer, B. C. (2025). Assimilating Novel Boundary Layer Observations from Dual-Polarization Radars to Improve Lower-Tropospheric Moisture and Torrential Rainfall Forecasts. *Monthly Weather Review*, 153(2), 309–326. <https://doi.org/10.1175/MWR-D-24-0154.1>
- Zheng, X., Guo, Y., Zhou, Z., & Wang, T. (2024). Improvements in land surface temperature and emissivity retrieval from Landsat-9 thermal infrared data. *Remote Sensing of Environment*, 315, 114471. <https://doi.org/10.1016/j.rse.2024.114471>
- Zhou, S., Williams, A. P., Berg, A. M., Cook, B. I., Zhang, Y., Hagemann, S., et al. (2019). Land–atmosphere feedbacks exacerbate concurrent soil drought and atmospheric aridity. *Proceedings of the National Academy of Sciences*, 116(38), 18848–18853. <https://doi.org/10.1073/pnas.1904955116>
- Zhu, Y., Liu, E., Mahajan, R., Thomas, C., Groff, D., Delst, P. V., et al. (2016). All-Sky Microwave Radiance Assimilation in NCEP’s GSI Analysis System. *Monthly Weather Review*, 144(12), 4709–4735. <https://doi.org/10.1175/MWR-D-15-0445.1>
- Zhu, Y., Todling, R., & Jin, J. (2021). Improving the Use of Surface-Sensitive Radiances in the GMAO Hybrid-4DEnVar System. Presented at the 23rd International TOVS Study Conference, Virtual. Retrieved from https://itwg.ssec.wisc.edu/wordpress/wp-content/uploads/2023/05/poster.2p.20.zhu_itsc23.pdf
- Zhu, Y., Todling, R., & Arnold, N. (2022). Observation Impact and Information Retention in the Lower Troposphere of the GMAO GEOS Data Assimilation System. *Monthly Weather Review*, 150(8), 2187–2205. <https://doi.org/10.1175/MWR-D-21-0334.1>
- Zhu, Y., Arnold, N. P., Yang, E.-G., Ganeshan, M., Salmun, H., Palm, S., et al. (2025). Utilizing PBL Height Data from Multiple Observing Systems in the GEOS System. Part I: Assimilation Framework. *Monthly Weather Review*, 153(3), 403–423. <https://doi.org/10.1175/MWR-D-24-0141.1>