

Review

Remote sensing of planetary boundary layer from ground and space: Structure, thermodynamics, and boundary layer clouds

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ABSTRACT

The planetary boundary layer (PBL) is a critical interface between Earth's surface and atmosphere, influencing atmospheric convection, weather patterns, and air quality. Recognized by the 2017 National Academies of Sciences, Engineering, and Medicine Earth Science Decadal Survey as an Incubation Targeted Observable, high-quality and effective observation of the PBL has become a priority. This paper reviews surface-based and satellite remote sensing techniques for characterizing PBL features, including PBL height (PBLH), boundary layer thermodynamics, turbulence, and boundary layer clouds (BLCs). These elements are treated as interconnected aspects of the PBL system, while recognizing that different instruments retrieve different physical manifestations of the PBL. The review summarizes recent advances and limitations in Micro-Pulse Lidar (MPL), Doppler lidar, Raman lidar, Differential Absorption Lidar (DIAL), ceilometers, wind profilers, GNSS Radio Occultation, radar, and hyperspectral sounders. These observations help trace dynamic processes within the PBL and link PBL structure to broader weather and climate processes. The review also highlights persistent observational gaps over oceans, remote land, and polar regions, where continuous surface-based profiling is sparse. By comparing instrument capabilities, practical limitations, and interpretation issues, this review emphasizes the need for integrated remote sensing approaches and careful definition of the retrieved PBL quantities.

1. Introduction

The planetary boundary layer (PBL), also known as the atmospheric boundary layer, plays a fundamental role in the interaction between the Earth's surface and atmosphere, influencing air quality, weather patterns, and the climate system (Stull, 1988; Driedonks, 1982; Barlow, 2014; Santanello et al., 2011). The PBL may extend from just above Earth's surface to several kilometers under favorable convective conditions, although most daytime PBL depths over land are commonly on the order of 1–1.5 km; its height and thermodynamic properties are crucial in mediating surface-atmosphere interactions, meteorology, and the environment (Garratt, 1994; Stull, 1988; Li et al., 2017a). In this review, PBLH is defined as the altitude separating the surface-influenced turbulent layer from the overlying free troposphere (FT), with the recognition that remote sensors may retrieve material PBLH, dynamical

PBLH, or thermal PBLH manifestations of this transition, i.e., the differences between PBL and FT composition, atmospheric flows, and temperature might not all occur at exactly the same elevation above the surface (Tan et al., 2025). Over land, the PBL can exhibit different thermodynamic conditions throughout the day, categorized here based on current PBL static stability structure as a convective boundary layer (CBL), neutral boundary layer (NBL), or stable boundary layer (SBL). A CBL is typically found during the daytime, with active thermals and strong turbulence, NBL conditions usually occur during transition periods or under stratiform cloud conditions, and an SBL commonly occurs at night, with weak turbulence and strong stratification (Liu and Liang, 2010).

Traditionally, radiosonde measurements have been used to provide vital data on PBL vertical structure, including temperature, humidity, pressure, and wind profiles (Seidel et al., 2010; Wilson et al., 2010; Guo

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et al., 2016, 2021a; Ko et al., 2019). Although radiosondes offer detailed profiles of these atmospheric variables, they cannot directly measure turbulence or fully characterize cloud layers, and sampling is extremely limited in time and location. Techniques involving tethered balloons, unmanned aerial vehicles (UAVs), and aircraft, despite their higher cost, have offered detailed profiles of turbulence and cloud microphysics, enriching our understanding of PBL processes. These in situ techniques provide highly accurate PBL information, but they suffer from infrequent measurements and limited spatial coverage, and thus generally do not capture the diurnal or spatial variability of PBLH. Remote sensing has increasingly filled these gaps by delivering relatively high-resolution observations over extended periods, allowing for more continuous profiling in both temporal and vertical dimensions (Illingworth et al., 2019; Cimini et al., 2020; Santanello et al., 2018; Wulfmeyer et al., 2018).

Advances in remote sensing technologies, using both ground-based and satellite-based instruments, have substantially improved our ability to observe the PBL, allowing more detailed measurements of its vertical extent and thermodynamic properties. These measurements also provide context for aerosol loading and light-absorption profiles, which influence radiative heating, stability, and aerosol-tracer interpretations of PBLH. Ground-based lidars and radars provide continuous vertical profiles that are necessary for understanding PBL diurnal development and mixing processes across diverse geographic and synoptic conditions (Eresmaa et al., 2006; Illingworth et al., 2019). Although lidars excel in capturing cloud boundaries and aerosol profiles, and radars are adept at observing precipitation and cloud evolution, obtaining adequate spatial coverage remains challenging (Luo et al., 2014). Satellite methods, including space-borne lidars, infrared (IR) and microwave sounders, and Global Navigation Satellite System (GNSS) radio occultation (RO), support climate analysis by providing PBLH, temperature, and water vapor profiles. They are especially valuable over oceans, remote land, and polar regions where continuous surface-based observations are limited, but they still suffer from limitations in vertical, horizontal, and temporal resolution and sensitivity to lower-tropospheric PBL structure (Illingworth et al., 2019; Cimini et al., 2020).

Accurate characterization of boundary layer clouds (BLCs), particularly in understanding their interactions with PBL thermodynamics and Earth's surface, is critical for comprehending cloud feedback mechanisms and their broader implications for climate sensitivity and weather patterns. Ground-based and satellite remote sensing technologies have emerged as important tools in this quest, enabling detailed observations of cloud evolution, thermodynamic properties, the complex interactions between cloud and PBL processes, and surface forcing. Studies have shown that surface fluxes significantly influence the formation and behavior of low clouds within the PBL, driving feedback loops that impact climate modeling and prediction (Golaz et al., 2002; Teixeira and Hogan, 2002; Betts, 2009; Zheng et al., 2020a). These issues are also central over oceans and polar regions, where marine stratocumulus, trade cumulus, and mixed-phase low clouds remain difficult to observe continuously and to represent in models (Wood, 2012; Bretherton, 2015; Morrison et al., 2012; Shupe et al., 2011). However, the complexity of these interactions, especially over land, where thermodynamic profiles exhibit notable variability, poses challenges for our current understanding (Pielke Sr. et al., 2011; Zhang and Klein, 2010; Helbig et al., 2021). Recognizing whether these clouds are coupled to the surface or decoupled is essential, as is quantifying cloud updrafts and their effects on PBL thermodynamics, highlighting the value of advanced remote sensing methodologies that can accurately assess these states and their effects on cloud formation and development (Su et al., 2023; Dong et al., 2015; Zheng and Li, 2019; Zheng et al., 2018).

Compared with existing reviews on PBL remote sensing (e.g., Kotthaus et al., 2023; Dang et al., 2019; Zhang et al., 2020), which focus primarily on specific elements such as PBL height, this review takes a comprehensive approach by considering different aspects of the PBL and emphasizing the interconnected nature of elements, including PBLH,

thermodynamics, and BLCs. As an overview of the objectives of this review, Fig. 1 presents a schematic representation of the diverse array of ground-based and space-borne remote sensing instruments used for PBL monitoring, highlighting their capabilities, limitations, and synergistic roles in observing and analyzing the PBL. Tables 1 and 2 offer summaries of measurement characteristics for surface-based and satellite-based instruments, respectively; supporting references are provided in the corresponding instrument-specific sections. The integration of data from various platforms is necessary for enhancing our understanding of the PBL. The NASA Decadal PBL Survey Incubation outlines an ambitious goal of creating a comprehensive global PBL observing system, addressing current gaps in our understanding and monitoring capabilities (Teixeira et al., 2021, 2025). In this context, our review aims to elucidate the different PBL parameters accessible through various remote sensing techniques, delineating their applications and limitations, and envisioning future advancements. It underscores the necessity of integrating remote sensing of PBLH, thermodynamics, and BLCs across various scales, as well as their implications for weather and climate.

This review is structured as follows: Section 2 discusses remote sensing of PBLH, covering technologies such as aerosol backscatter lidars (e.g., Micro-Pulse Lidar, MPL), Doppler lidars, ceilometers, radar wind profilers (RWP), and GNSS RO. Section 3 focuses on remote sensing of boundary layer thermodynamics, including thermodynamic profiles derived from Raman lidar (RL), DIAL, hyperspectral sounders, and vertical velocity measurements from Doppler lidar. Section 4 examines remote sensing of cloud occurrence, fraction, and updraft for BLCs. Section 5 discusses challenges and perspectives, and Section 6 provides concluding remarks.

2. Remote sensing of planetary boundary layer height

Both ground-based and space-borne remote sensing instruments have been widely used to estimate PBLH, each offering distinct strengths and limitations. A summary of the key capabilities and limitations of these instruments is provided in Table 1 (ground-based) and Table 2 (satellite-based), which synthesize the techniques discussed throughout Sections 2–4; supporting references are cited in the corresponding subsections. A more detailed discussion of these limitations is provided in Section 5. Because PBLH is a derived quantity rather than a directly measured parameter, the retrieved height depends on the observed tracer or state variable (e.g., aerosol backscatter, humidity, temperature, wind, or turbulence) and the algorithm used. Among ground-based systems, ceilometers provide the most operationally widespread observations, though with sensitivity that depends on aerosol loading, wavelength, SNR, and overlap characteristics. Elastic backscatter lidars such as MPL offer improved vertical resolution, whereas Doppler lidars add wind profiling and turbulence measurements essential for identifying entrainment zones, the transition layers near the PBL top where boundary-layer and free-tropospheric air mix. RWPs complement lidar by continuously measuring vertical wind profiles, enabling retrievals even under low aerosol conditions, although with coarser vertical resolution and important near-surface limitations. Representative diurnal PBLH retrievals from MPL, Doppler lidar, and RWP are shown in Fig. 2. From space, backscatter lidars such as CALIOP on CALIPSO and the recently launched ATLID on EarthCARE (Wehr et al., 2023) extend aerosol and cloud profiling globally, whereas GNSS-RO provides complementary information about refractivity and moist thermodynamic structure. Aerosol amount and light-absorption profiles can also affect PBL thermal structure and the interpretation of aerosol-based retrievals, although a detailed review of aerosol optical-property profiling is outside the scope of this paper.

A useful way to compare PBLH retrievals is to distinguish three related but not necessarily identical quantities. Material PBLH, often expressed as aerosol or tracer-based PBLH, is inferred from tracers such as aerosol backscatter or water vapor; dynamical PBLH is inferred from

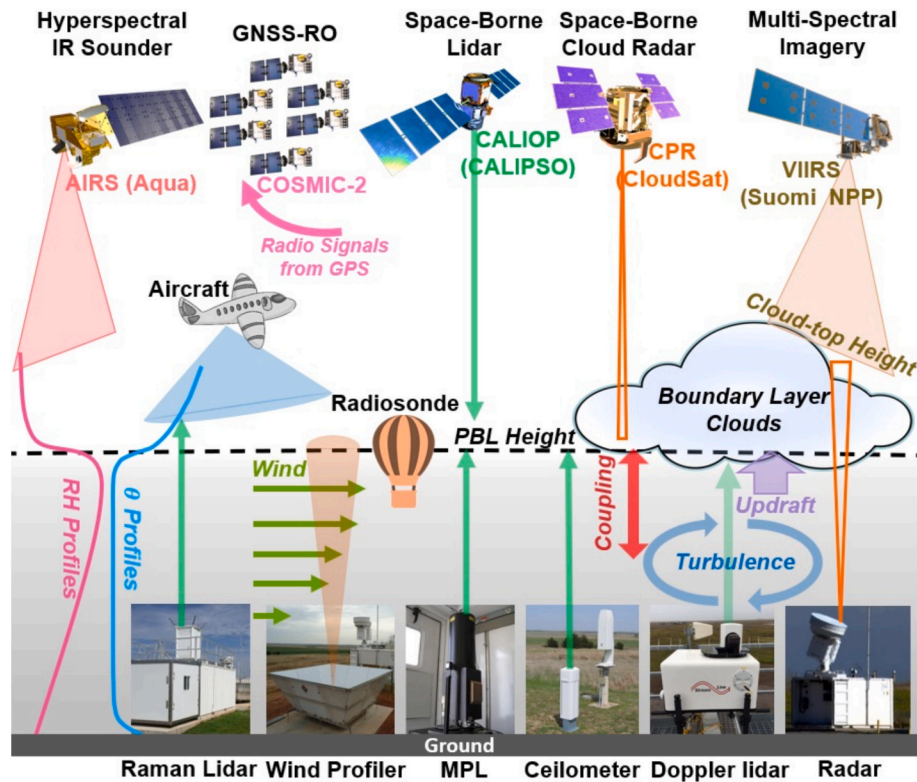


Fig. 1. Schematic representation of the various remote sensing instruments (exemplary, not exclusive) used for the monitoring of the Planetary Boundary Layer (PBL). The diagram illustrates the deployment of ground-based Raman lidar (RL), Radar Wind Profiler (RWP), Doppler lidar, Micro-Pulse Lidar (MPL), Ceilometer, and Cloud Radar instruments, along with satellite sensors, including Hyperspectral Infrared Sounder (e.g., AIRS on Aqua), GNSS-RO (e.g., COSMIC-2), Space-Borne Lidar (e.g., CALIOP on CALIPSO), Space-Borne Cloud Radar (e.g., CPR on CloudSat), and Multi-Spectral Imagery (VIIRS on Suomi NPP). Notably, radar and lidar can also be deployed aboard aircraft, extending their observational reach to provide more reliable and continuous information for targeted areas. In-situ measurements from radiosondes and aircraft further serve as critical validation tools for remote sensing data. These instruments collectively contribute to the observation of PBL height, thermodynamics, turbulence, and boundary layer clouds (BLCs). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

turbulence, wind shear, or vertical velocity variance; and thermal PBLH is inferred from potential temperature, virtual potential temperature, refractivity, or inversion structure. Differences among these products do not necessarily indicate retrieval failure, because these instruments are sensing different aspects of the PBL top.

2.1. Ceilometer

Ceilometers, which utilize laser-based atmospheric lidar techniques, have been the most widely deployed and used instruments for determining PBLH due to their relatively low cost compared to other remote sensing techniques (e.g., MPL). Primarily designed for cloud-base height detection and atmospheric profiling, ceilometers provide valuable information on PBLH because of their operational simplicity and suitability for routine, unattended operation. These devices have been deployed across many regions, enabling continuous monitoring of atmospheric aerosols and cloud structures, with an emphasis on elucidating the complexities of the PBL (Kotthaus and Grimmond, 2018).

One of the key advantages of ceilometers lies in their automated, unattended operation, which enables persistent long-term observations of PBLH. Their widespread deployment, especially as part of meteorological networks, has facilitated monitoring of aerosol structure and cloud evolution within the PBL (Kotthaus and Grimmond, 2018). In addition, ceilometers possess an advantage in detecting and monitoring the lower atmospheric layers, providing essential data on shallow PBL structures due to their ability to achieve full optical overlap at lower levels, unlike high-power lidar systems (Kotthaus et al., 2016; Caicedo et al., 2020).

Algorithms commonly applied to other lidar systems, such as the wavelet covariance transform (WCT) and gradient methods, can also be used to retrieve PBLH from ceilometer data (Caicedo et al., 2017). Haeffelin et al. (2012) evaluated ceilometer-derived PBLH and demonstrated good agreement with radiosonde data for a limited sample. Using ceilometers across the ARM observational network, Zhang et al. (2022) compared ceilometer-derived PBLH with radiosonde measurements under different conditions, finding good agreement under NBLs and CBLs, but noting challenges in SBLs and over ocean surfaces, highlighting the need for additional, advanced estimation methods.

Despite their widespread application and the apparent concordance of ceilometer-derived PBLH with radiosonde measurements, challenges persist, particularly regarding spatial coverage and variability across instruments, sites, and retrieval settings. Accurate PBLH estimation from ceilometer measurements requires validation under diverse atmospheric conditions and geographical landscapes to ensure data robustness (Haeffelin et al., 2012; Hama et al., 2012). As relatively low-power laser systems, ceilometers have lower SNR than many research lidars, particularly in environments characterized by low aerosol loading or elevated altitudes (Heese et al., 2010). Ceilometer observations also do not form a single uniform class: common systems differ in wavelength, maximum useful range, overlap behavior, and sensitivity to water vapor and aerosol backscatter. These differences matter most for shallow SBLH retrievals and clean marine or polar conditions, where the actual layer height can be close to, or below, the near-surface overlap/blind-zone region.

Table 1

Summary of ground-based instruments for monitoring parameters related to PBL. T and Q profiles refer to temperature and humidity profiles within the PBL (up to 4 km). Uncertainties refer to representative case-level estimates for the listed parameters.

Ground-based Instrument	Parameters / derived products	Vertical Resolution	Representative case-level uncertainty	Strengths	Limitations
Doppler lidar	PBLH	<50 m	100–400 m	High vertical resolution; profiles PBL turbulence	Coherent systems depend on aerosol backscatter/SNR; blind zone; threshold/scan-strategy and averaging choices; ineffective in heavy precipitation
Doppler lidar	Vertical velocity	<50 m	Lack of ground-truth	High vertical resolution; profiles PBL turbulence	Coherent systems depend on aerosol backscatter/SNR; blind zone; threshold/scan-strategy and averaging choices; ineffective in heavy precipitation
Micro-Pulse Lidar (MPL)	Cloud Mask	10–30 m	<100 m	High vertical resolution; reliable cloud base	Overlap correction; reduced shallow SBLH accuracy; cloud/precipitation attenuation
Micro-Pulse Lidar (MPL)	PBLH	10–30 m	100–500 m	High vertical resolution; reliable cloud base	Overlap correction; reduced shallow SBLH accuracy; cloud/precipitation attenuation
Ceilometer	Cloud-base Height	10–50 m	<100 m	Automated operation; portable; high vertical resolution	Model/wavelength dependent; low SNR in clean air; overlap/blind-zone effects; residual-layer ambiguity; ineffective in precipitation
Ceilometer	PBLH	10–50 m	200–500 m	Automated operation; portable; high vertical resolution	Model/wavelength dependent; low SNR in clean air; overlap/blind-zone effects; residual-layer ambiguity; ineffective in precipitation
Radar Wind Profiler (RWP)	Wind	100–300 m	1–2 m/s	All-weather operation; high detection range (~10 km)	Ground clutter; limited data at low altitudes; caution for afternoon CBL; insects/hydrometeors can affect SNR
Radar Wind Profiler (RWP)	PBLH	100–300 m	200–500 m	All-weather operation; high detection range (~10 km)	Ground clutter; limited data at low altitudes; caution for afternoon CBL; insects/hydrometeors can affect SNR
Raman lidar (RL)	T profile	10–60 m	1–2 K	High vertical resolution; fine vertical structures	Limited range during daytime; blind zone; ineffective in precipitation; requires calibration
Raman lidar (RL)	Q profile	10–60 m	<20%	High vertical resolution; fine vertical structures	Limited range during daytime; blind zone; ineffective in precipitation; requires calibration
Raman lidar (RL)	PBLH	10–100 m	Definition dependent	Thermal and material PBLH context	Useful for inversion/moisture-gradient diagnostics; limited by daytime range, overlap, clouds, and calibration
DIAL	Q profile	10–100 m	System and humidity dependent	High vertical resolution water vapor profiling	Sensitive to absorption-line choice, high water vapor, attenuation, clouds, and wavelength stability
Atmospheric Emitted Radiance Interferometer (AERI)	T profile	100 m (below 3 km)	<1–2 K for clear sky; retrieval dependent	High accuracy for clear sky; long-term stability	Large uncertainties for cloudy cases; limited retrieval depth (~3 km)
Atmospheric Emitted Radiance Interferometer (AERI)	Q profile	100 m (below 3 km)	Retrieval dependent; larger without auxiliary water vapor	High accuracy for clear sky; long-term stability	Large uncertainties for cloudy cases; limited retrieval depth (~3 km)
Microwave Radiometer (MWR)	T profile	100–500 m	~2 K	Useful in cloudy conditions; continuous operation	Coarse vertical information; calibration/radome wetting issues; precipitation sensitivity
Microwave Radiometer (MWR)	Q profile	100–500 m	Retrieval dependent	Useful in cloudy conditions; continuous operation	Coarse vertical information; calibration/radome wetting issues; precipitation sensitivity
Cloud Radar (millimeter wavelengths)	Cloud Mask	<100 m	N.A.	Reliable cloud top; detects multiple cloud layers	Ground clutter; attenuation by heavy precipitation
ARSCL: combining lidar, radar, ceilometer and MWR	Cloud Mask	<100 m	N.A.	Comprehensive datasets; reliable cloud base and top	Attenuation by heavy precipitation

2.2. Ground-based elastic backscatter lidar

Ground-based elastic lidar technology, such as MPL or HSRL, operates by emitting laser pulses and measuring the intensity of light scattered back by clouds, atmospheric aerosols and gas molecules. The resulting backscatter profiles are valuable for PBLH monitoring, and the technique has been validated through various studies (Hageli et al., 2000; Sawyer and Li, 2013). Despite limitations in spatial coverage, backscatter lidar datasets, along with other instruments such as Raman lidars, have been deployed fairly widely in projects like the NASA Micro-Pulse Lidar Network (MPLNET; Lewis et al., 2013), the Department of Energy's Atmospheric Radiation Measurement (ARM) program (Campbell et al., 2002), the European Aerosol Research Lidar Network (EARLINET; Pappalardo et al., 2014), and the Latin American Lidar Network (LALINET; Antuña-Marrero et al., 2017), contributing PBLH retrievals over different regions. One strength of backscatter lidars lies in their high vertical resolution (typically ~30 m) and rapid temporal

sampling (less than 1 min), which allow them to detect sharp gradients in aerosol backscatter or wavelet transform signatures near the PBL top (Toledo et al., 2014). Compared with most operational ceilometers, MPL and other research elastic backscatter lidars are generally optimized for aerosol and cloud backscatter profiling with higher sensitivity and more flexible processing, whereas ceilometers are lower-power automated systems designed primarily for routine cloud-base detection; both can support PBLH retrieval, but their overlap, SNR, wavelength, and calibration characteristics differ.

A diverse array of methods for deriving PBLH from such lidar data has been developed over the years, starting from subjective visual inspections (Boers et al., 1984; Nelson et al., 1989), moving to sophisticated algorithms like the wavelet transform and changes in the depolarization ratio (Brooks, 2003), to the use of more recent ideas such as image edge detection, cluster analyses, and layer tracking (Cohn and Angevine, 2000; Bravo-Aranda et al., 2017). Retrievals of lidar-PBLH are based on the vertical distribution of aerosols, whose backscattering of

Table 2

Summary of satellite sensors for parameters related to PBL. “V” denotes vertical resolution, and “H” denotes horizontal resolution. Uncertainties are representative product-level estimates for the listed parameters.

Satellite Sensors	Parameters	Vertical and Horizontal Resolution	Representative product uncertainty	Strengths	Limitations
Hyperspectral IR (e.g., AIRS on Aqua)	T profile	V: 1–2 km; H: 14 km	1 K	Effective in clear-sky conditions	Clear sky; limited effective vertical resolution; prior/averaging-kernel dependence
Hyperspectral IR (e.g., AIRS on Aqua)	Q profile	V: 1–2 km; H: 14 km	10%	Effective in clear-sky conditions	Clear sky; limited effective vertical resolution; prior/averaging-kernel dependence
Microwave Sounder (e.g., ATMS on Suomi NPP)	T profile	V: 2–4 km; H: 40 km	1–2 K	Cloud penetration capability	All-weather context but insufficient vertical resolution for many PBL temperature inversions and moisture gradients
Microwave Sounder (e.g., ATMS on Suomi NPP)	Q profile	V: 2–4 km; H: 40 km	10–20%	Cloud penetration capability	All-weather context but insufficient vertical resolution for many PBL temperature inversions and moisture gradients
GNSS-RO	T profile	V: 200–500 m; H: 100 km	1–2 K	Relatively high vertical resolution	Limited horizontal resolution for sharp gradients; coupled T and Q retrievals; ducting effects
GNSS-RO	Q profile	V: 200–500 m; H: 100 km	0.5–1 g/kg	Relatively high vertical resolution	Limited horizontal resolution for sharp gradients; coupled T and Q retrievals; ducting effects
GNSS-RO	PBLH	V: 200–500 m; H: 100 km	100–200 m	Relatively high vertical resolution	Limited horizontal resolution for sharp gradients; coupled T and Q retrievals; ducting effects
Lidar (e.g., CALIOP on CALIPSO)	PBLH	V: 30 m	100–300 m	High vertical resolution (~30 m); detects aerosol layers	Limited track coverage; low SNR; daytime background; cloud attenuation; residual-layer attribution
Radar (e.g., CPR on CloudSat)	Cloud Mask	V: 200–500 m	N.A.	Penetration through cloud layers	Limited spatial coverage; attenuation by heavy precipitation
Multi-spectral Imagery (e.g., VIIRS on Suomi NPP)	CTH	H: 750 m (raw)	200–300 m	Broad area coverage; retrieves cloud-top properties	Passive imagery provides cloud-top/horizontal context; cloud base, coupling, and updraft estimates require auxiliary PBLH/LCL or active-sensor information
Multi-spectral Imagery (e.g., VIIRS on Suomi NPP)	Inferred Cloud-base Updraft	H: 750 m (raw)	Assumption dependent; limited validation	Potential for coupled BLC regimes	Passive imagery provides cloud-top/horizontal context; cloud base, coupling, and updraft estimates require auxiliary PBLH/LCL or active-sensor information

photons is a good indicator of the PBLH for well-mixed CBLs or NBLs. However, during SBL or transition periods, lidar-PBLH retrievals tend to return the residual layer height, which may reflect the remnants of the PBL thermodynamic state from the previous day. The multiple techniques used for deriving PBLH from lidar highlight the complexity in accurately detecting PBLH across varying atmospheric conditions (Li et al., 2017a; Zhang et al., 2018).

The methodology for PBLH detection from lidar data involves two essential steps: identifying potential boundaries of aerosol, residual, or cloud layers, and correctly attributing these detected layers to the PBL structure. This approach has led to the categorization of aerosol-based retrieval methods into first and second generations, depending on whether they primarily focus on layer detection or the more complex task of layer attribution (Emeis et al., 2008; Dang et al., 2019).

For the first critical step of identifying potential layer boundaries, various indicators have been employed, including negative vertical gradients, inflection points, 2D edge detection, WCT, and spatio-temporal variance, among others (Sicard et al., 2006; Emeis et al., 2008; Morille et al., 2007; Granados-Muñoz et al., 2012). These methods vary in reliability across the diurnal evolution of the PBL, with the strongest negative gradient in attenuated backscatter often marking the PBLH. The interaction between moist air in the PBL and dry free tropospheric air creates areas of strong variance, further complicating the detection process (Menut et al., 1999; Lammert and Bösenberg, 2006).

Layer attribution, the second critical step, employs both first and second-generation techniques. First-generation methods might use the strongest negative gradient or the first negative gradient above the ground to identify the top of the layer of interest. Combining multiple indicators—such as the maximum negative gradient height and the height of maximum variance—has proven effective in separating the PBLH from lofted or decoupled aerosol layers, both during daytime and nighttime conditions (Martucci et al., 2010; Morille et al., 2007). Recent advancements, such as the Different ThermoDynamic Stabilities (DTDS)

algorithm, improve upon traditional methods by integrating gradient-based approaches with diurnal cycle constraints, enhancing both vertical consistency and temporal continuity of PBLH retrievals (Su et al., 2020; Roldán-Henao et al., 2024a).

Recent retrieval methods include Kalman filters and machine-learning classifiers for lidar-based PBLH detection tailored to different applications (Krishnamurthy et al., 2021; Peng et al., 2023). For instance, extended Kalman filters enable real-time retrieval in low SNR scenarios, whereas K-means cluster analysis classifies aerosol or cloud layers to distinguish between well-mixed and stratified layers (Toledo et al., 2014; Lange et al., 2013; Wang et al., 2021). Supervised Ada-Boost algorithms improve detection accuracy by integrating multiple classifiers to identify diurnal transitions and PBL structure changes (Rieutord et al., 2021). These developments show that the choice of gradient, WCT, threshold, variance, fuzzy-logic, Kalman-filter, or AI/ML method should be guided by the target PBLH definition and the observing regime, rather than by a single universal ranking of algorithms.

Because published uncertainty estimates are usually derived from different sites, reference datasets, atmospheric regimes, and algorithm settings, the ranges in Table 3 should be interpreted as representative rather than as a controlled cross-method benchmark (e.g., Haeffelin et al., 2012; Caicedo et al., 2017; Bonin et al., 2018; Kotthaus et al., 2023).

The comparison in Table 3 highlights that no single method provides a universally optimal estimate of PBLH. Aerosol-based approaches perform well in convective conditions with strong gradients but can fail in clean or weakly stratified environments. Doppler lidar provides a more direct measure of boundary-layer dynamics but depends on sufficient turbulence. Thermodynamic methods can better capture stable boundary layers but are limited by vertical resolution and inversion strength. Satellite-based approaches offer valuable large-scale coverage but lack the vertical and horizontal resolution required for detailed boundary-layer structure. These differences reflect the fact that each

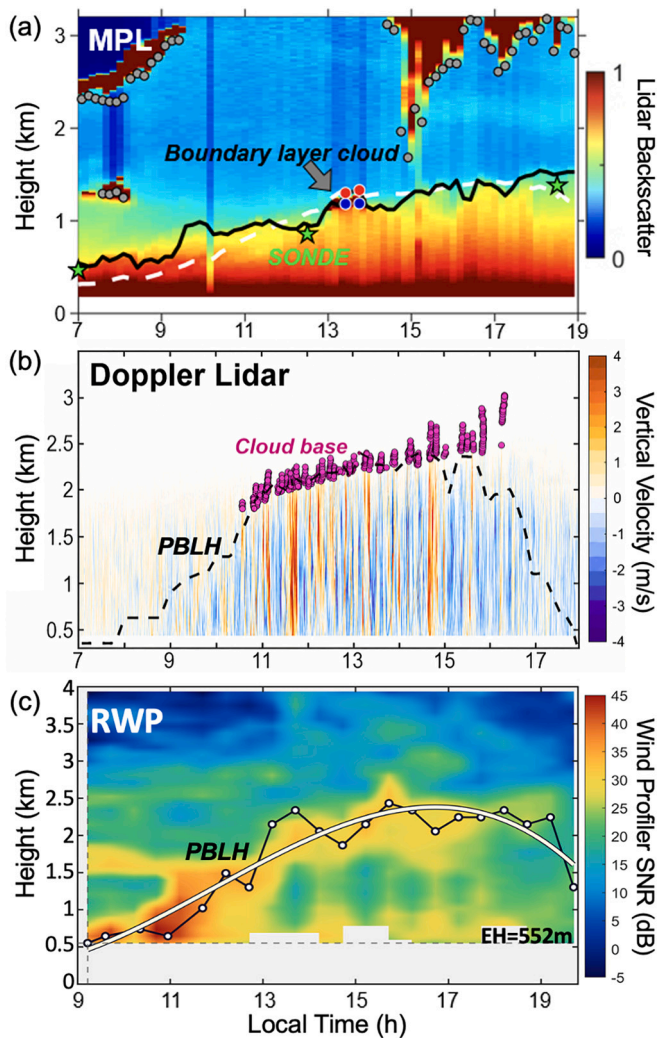


Fig. 2. Diurnal variation of PBLH as detected by multiple ground-based remote sensing instruments. (a) MPL backscatter profile providing a normalized backscatter signal. Black lines and green stars indicate PBLH retrieved from MPL and radiosonde respectively; red and blue dots represent cloud-top heights (CTHs) and cloud-base heights (CBHs) of coupled clouds, with gray dots for CBHs of decoupled clouds, and dashed white lines showing lifted condensation levels (LCLs) derived from collocated thermodynamic information. Panel (a) is adapted from Su et al. (2022). (b) Doppler lidar vertical velocity profile with colour shading indicating velocity, dashed black lines marking the derived PBLH, and magenta dots denoting CBH. Panel (b) is adapted from Lareau et al. (2018). (c) RWPs signal-to-noise ratio (SNR) showing the diurnal evolution of PBLH at a station in Germany (52.21°N, 14.13°E), with the black curve and open circles representing PBLH retrieved by the RWP algorithm, and the white line showing a third-degree polynomial smoothing of that curve. Panel (c) is plotted using the data from Salmun et al. (2023). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

method effectively retrieves a different physical manifestation of the PBL top, underscoring the importance of selecting retrieval approaches based on the scientific objective and observing conditions.

2.3. Doppler lidar

Over recent decades, Doppler lidar has become one of the major tools for studying PBL turbulence. With a vertical resolution of 10–50 m and a temporal resolution of less than one minute, Doppler lidar can capture the fine-scale variability of vertical wind velocity within the PBL, positioning it as an important instrument for characterizing turbulent PBL

processes (Lothon et al., 2006; O'Connor et al., 2010; Trümner et al., 2011; Berg et al., 2017). Unlike elastic backscatter lidars and ceilometers, which primarily infer layer structure from backscatter intensity, Doppler lidar retrieves radial velocity from the frequency shift of the backscattered signal and therefore provides a more direct constraint on wind and turbulence.

Doppler lidar observations of wind and turbulence proxies have significantly advanced quantitative assessment of boundary-layer mixing. For instance, Doppler lidar can identify the entrainment zone through high SNR observations (Trümner et al., 2011). Doppler lidar's utility extends to the detection of PBLH, employing methods that rely on wind profile observations (Emeis et al., 2008; Tucker et al., 2009). These methods can distinguish between buoyancy-driven and shear-driven turbulence, which is key to determining whether the CBL is connected to the surface. However, challenges remain in accurately detecting the residual layer height due to intermittent turbulence, underscoring the complexity of layer detection in the PBL (Pichugina and Banta, 2010). Several approaches have been applied to determine PBLH using Doppler lidar data. For example, Balsley et al. (2006) examined high-resolution profiles of small-scale turbulence to define the top of SBL using parameters derived from Doppler lidar. Tucker et al. (2009) proposed a method to estimate the mixing height based on turbulence, wind shear, and aerosol profiles. Bonin et al. (2018) further demonstrated an automated composite fuzzy-logic approach for estimating mixing height from Doppler lidar observations, illustrating how multi-indicator methods can reduce ambiguity under operational conditions.

Under convective conditions, the vertical velocity variance observed by Doppler lidar provides a useful measure of mixing within the CBL, with PBLH often defined by a threshold value for vertical velocity variance. This method has seen varying implementations, using both absolute and relative threshold values, demonstrating the adaptability of Doppler lidar data for PBLH detection. However, the selection of an appropriate threshold is a key step for the retrievals, as it can influence the sensitivity of PBLH detection, especially during periods of decaying turbulence (Tucker et al., 2009; Schween et al., 2014).

The application of Doppler lidar in PBL research has primarily focused on the characterization of PBL turbulence (Eberhard et al., 1989; Gal-Chen et al., 1992; Manninen et al., 2018). High-order moments of Doppler velocity and backscatter data have been used to retrieve information on the turbulent PBL (Ansmann et al., 2010; O'Connor et al., 2010). The integration of Doppler lidar network data has enabled statistically robust climatological studies of PBL turbulence. Combining these data with observations from MPL and ceilometers, which offer broader spatial coverage and sensitivity to aerosol gradients, further enhances our understanding of PBL structure and supports accurate PBLH detection and diurnal tracking (Pappalardo et al., 2014; Caumont et al., 2016; Späth et al., 2022).

The synergy of Doppler lidar with other lidar technologies, such as elastic lidar, has enhanced our ability to observe complex atmospheric variables like vertical particle flux, further demonstrating the versatility of Doppler systems (Wandinger et al., 2004; Engelmann et al., 2008). Through both standalone applications and synergistic operations with other lidar technologies, Doppler lidar is helpful for elucidating the complexities of the turbulence, with potential applications extending to space-borne platforms (Witschas et al., 2020).

2.4. Radar wind profiler

Ground-based RWPs are increasingly used for estimating the PBLH, offering continuous observations that are essential for understanding the evolution of vertical wind profiles within the PBL (Emeis et al., 2008; Hennemuth and Lammert, 2006). RWPs, through their continuous measurement capabilities, have addressed some of the limitations inherent in most lidar systems. Although lidars can offer temporally continuous aerosol vertical profiles, RWPs extend this by providing continuous wind observations directly linked to the turbulent structures

Table 3

Comparison of common PBLH retrieval methods. Typical uncertainties are representative values reported in published studies or reviews and are not a uniform accuracy ranking across identical cases.

Method / Approach	Physical basis	Application conditions	Key limitations	Typical uncertainty / confidence	Recommended use
Gradient method (lidar/ceilometer)	Aerosol backscatter gradient	Convective BL; strong aerosol contrast	Fails in clean air; residual-layer ambiguity	± 100 –300 m; medium	Operational first-order PBLH
Wavelet covariance transform (WCT) method	Multi-scale gradient detection	Noisy signals; layered structures	Sensitive to weak gradients and attribution choices	± 150 –300 m; medium	Robust alternative to simple gradients
Variance/threshold method	Signal variability or vertical-velocity variance	Convective turbulence; automated processing	Weak signal or weak turbulence regimes	± 150 –300 m; medium-low	Simple automated detection
Doppler-lidar turbulence method	Turbulence, wind shear, and vertical velocity	Active turbulent BL	Weak turbulence; stable BL; aerosol/SNR limits	± 100 –200 m for turbulent BL; medium-high	Dynamical PBLH and process studies
Thermodynamic method (MWR, Raman lidar, RASS)	Temperature, humidity, or refractivity profiles	Strong inversions; stable BL context	Weak inversions; coarse or smoothed vertical resolution	± 50 –200 m in strong cases; medium	Stable BL and complementary estimates
Satellite-based method (passive/active)	Radiance, backscatter, or refractivity profiles	Large-scale climatology	Coarse vertical/horizontal resolution; sampling gaps	± 300 –1000 m; sensor dependent; low-medium	Regional/global patterns

within the PBL, albeit typically with coarser spatial resolution than Doppler lidars but better all-weather performance and lower sensitivity to aerosol content (Molod et al., 2015; Emeis et al., 2008).

Based on the SNR data, RWP can estimate PBLH using various algorithms (Solanki et al., 2022; Liu et al., 2019; Bianco et al., 2008). This has led to the development of algorithms specifically designed for PBLH retrieval from RWP measurements, highlighting the evolving sophistication of these methods (Cohn and Angevine, 2000; Singh et al., 2016). Among the algorithms employed, the peak detection algorithm and the WCT method have been notable for their early application to RWP data for PBLH determination. The peak detection algorithm, for example, identifies the PBLH by locating the strongest signal peaks in the SNR profiles, a method further refined by the integration of fuzzy logic algorithms to mitigate errors introduced by humidity gradients (Bianco and Wilczak, 2002; Compton et al., 2013). Subsequent improvements, such as incorporating Doppler spectral width into the fuzzy logic algorithm, have enhanced inversion accuracy under sunny conditions, although challenges remain under cloudy conditions (Bianco et al., 2008). In some cases, collocated Doppler lidar observations have been used to constrain variability in turbulence-scale motions, offering complementary insights under convective boundary layers or when turbulence intermittency makes single-instrument retrievals more uncertain.

The WCT method represents another significant advancement, initially developed for estimation from ground-based lidar data, but its application to RWP data has illuminated the temporal evolution of the PBLH over various terrains (Compton et al., 2013; Singh et al., 2016). In addition, Salmun et al. (2023) present a new global dataset of PBLH estimates retrieved from RWPs, called Global Radar Wind Profiler PBLH (GRWP-PBLH). This dataset was created using an existing algorithm applied to archived SNR data from networks, specifically those compiled and formatted by the United Kingdom Met Office from approximately 400 stations worldwide, that report to the British Atmospheric Data Centre and cover 26 countries, with data available since 2009. Meanwhile, the RWP network in China, operated by the China Meteorological Administration, comprises 134 stations providing continuous vertical wind profiles (Guo et al., 2021b; Liu et al., 2024).

The existing networks of RWPs demonstrate the extensive coverage and long-term utility of this technology, enabling detailed investigation into PBL wind profiles. At present, however, RWP-based PBLH retrieval remains less mature and less reliable than lidar- or radiosonde-based approaches, and retrievals should be interpreted cautiously, especially under afternoon convective conditions and in scenes affected by hydrometeors, insects, humidity gradients, or ground clutter. In these cases, the strongest SNR feature may not correspond to the actively mixed-layer top, and the lowest reliable gates may miss shallow SBLs because of low-level sampling constraints. As technologies evolve,

including the integration of radio acoustic sounding systems (RASS) for enhanced temperature profiling (Chandrasekar et al., 2003), applications of ground-based RWPs in PBL research continue to expand, particularly as part of multi-instrument networks rather than as stand-alone references.

2.5. Space-borne backscatter lidar

Space-borne backscatter lidar, particularly the CALIOP aboard the CALIPSO satellite, has the potential to observe the PBLH on a global scale by using backscatter signals with a vertical resolution of 30 m in the lower troposphere to capture the vertical distributions of clouds and aerosols (Winker et al., 2007). Compared with ground-based instruments, space-borne lidar can cover extensive spatial regions, albeit with a lower SNR due to the long distance the signals travel and limitations to the near-surface sensitivity of the backscatter (Yorks et al., 2011). CALIOP's position in the Afternoon satellite constellation (A-train) enabled it to operate in a Sun-synchronous polar orbit with an equatorial crossing time of 1:30 am/pm local time for PBL analysis from 2006 to 2023. This operational mode, combined with its ability to measure the total attenuated backscatter coefficient with high resolution, enables detailed assessments of atmospheric processes, including the identification of PBLH using variations in backscatter profiles (Winker et al., 2009). Because sunlight scattered back to space reduces daytime signal quality, CALIOP SNR was generally much greater at night than during the day.

Jordan et al. (2010) pioneered the use of CALIOP data for PBLH estimation, employing a method based on detecting a local maximum in the vertical standard deviation (MSD) of lidar backscatter at the PBL top. Subsequent modifications and validation of this method have confirmed the feasibility of the MSD method for PBLH determination, demonstrating reasonable agreement with results derived from radiosonde and ground-based MPL measurements (McGrath-Spangler and Denning, 2012; Liu et al., 2015; Zhang et al., 2016). Furthermore, WCT, a method proven effective with ground-based measurements, has been applied to CALIOP data (Su et al., 2017a). Su et al. (2018) integrated the MSD and WCT techniques to retrieve PBLH from CALIOP. Fig. 3 shows the climatology of seasonal variability in PBLH from CALIOP data and MERRA-2 reanalysis data (Gelaro et al., 2017), displaying the spatial distribution of seasonal mean PBLH with interpolated maps. The overall climatological patterns of CALIOP PBLH align with reanalysis, but the spatial and temporal sampling should be interpreted as climatological context rather than local process-scale monitoring, because residual layers, cloud attenuation, low SNR, and fixed overpass times can all affect PBLH attribution.

Despite CALIOP's advances, its sun-synchronous orbit restricts observations to fixed times, leaving gaps in diurnal PBLH understanding.

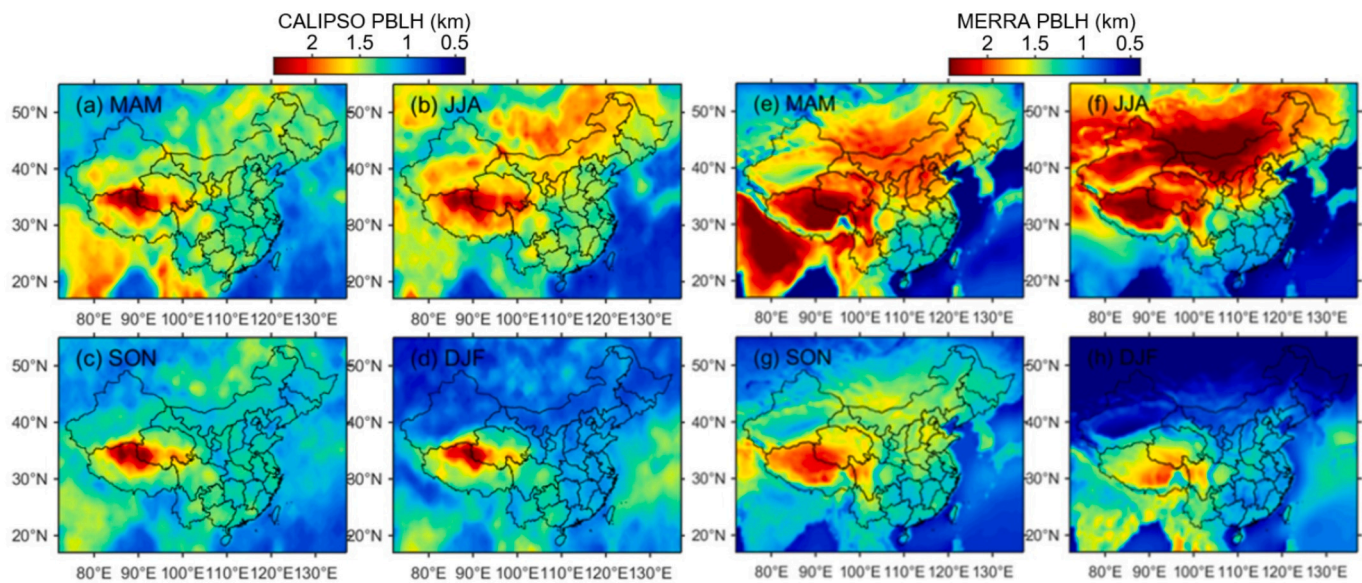


Fig. 3. Spatial distributions of climatological mean PBLH over south and east Asia derived from CALIOP for (a) March–April–May (MAM), (b) June–July–August (JJA), (c) September–October–November (SON), and (d) December–January–February (DJF). Spatial distributions of climatological mean of early-afternoon PBLH obtained from MERRA-2 for (e) MAM, (f) JJA, (g) SON, and (h) DJF during the period 2006–2016. Adapted from Su et al. (2018).

The introduction of the Cloud Aerosol Transport System (CATS) lidar on the International Space Station began to address these gaps, offering range-resolved profiles of aerosols and clouds across various times of day. This advancement holds the promise of more comprehensive temporal observations, allowing for the generation of approximate diurnal cycles of PBLH after extended periods of data collection (Yorks et al., 2016).

Recent studies utilizing CATS data have underscored the instrument's value in exploring PBLH across different times and conditions, providing new insights into the temporal variability and governing mechanisms of PBL processes on a near-global scale (Palm et al., 2021; Roldán-Henao et al., 2024b). NASA's CATS mission lasted from February 2015 to November 2017, providing 33 months of operation, and offering rich information on PBLH diurnal cycles from the space-borne lidar. These efforts using space-borne lidars highlight the ongoing evolution of technology and its role in advancing PBLH detection. Space-based lidar observations have enhanced our understanding of the PBL by providing comprehensive global PBLH climatologies, revealing aerosol vertical distributions within the PBL, and establishing relationships between PBLH and air quality (Su et al., 2018; Li et al., 2023a; Sun et al., 2019).

2.6. GNSS radio occultation

The advent of GNSS-RO technology has opened new avenues for the study of the PBLH. Recognizing the potential of GNSS-RO to sense the moist thermodynamic structure of the PBL early on (Melbourne et al., 1994), advancements have since been made to overcome initial limitations in signal dynamics caused by fine-scale variability of water vapor in the moist lower troposphere. The introduction of the Constellation Observing System for Meteorology, Ionosphere, and Climate (COSMIC) mission in 2006, which utilized open-loop tracking, marked an improvement in the ability of GNSS-RO to penetrate and retrieve data down to the PBL (Ao et al., 2003; Sokolovskiy et al., 2006).

The core principle of GNSS-RO lies in measuring the bending of radio signals as they pass through the Earth's stratified atmosphere. These bending angles are used to derive refractivity profiles via Abel inversion, under the assumption of a spherically symmetric atmosphere (Ao et al., 2009). From these profiles, vertical gradients in temperature and moisture can be inferred, enabling detection of the PBL top. Although the technique offers high vertical resolution (approximately 100–200

m), its horizontal resolution remains relatively coarse, and humidity estimates can carry larger uncertainties (Li et al., 2020).

The COSMIC mission, alongside subsequent missions of opportunity that supplemented data following COSMIC spacecraft issues in 2013, has provided a dataset spanning from June 2006 to December 2019 (Anthes et al., 2008; Kalmus et al., 2022). The launch of COSMIC-2 (FORMOSAT-7) in June 2019 has since produced global PBLH-related climatology studies, further contributing to weather prediction and atmospheric research with enhanced GNSS RO observations (Nelson et al., 2021; Schreiner et al., 2020).

Basha et al. (2019) provided a 10-year GNSS-RO climatology of PBLH with a coarser resolution of 5 degrees, further contributing to our understanding of PBL climatology. Furthermore, Kalmus et al. (2022) presented a PBLH climatology utilizing nearly 15 years of GNSS-RO data, representing a long-term GNSS RO-based PBLH climatology, and offering a PBLH horizontal resolution of 2 degrees. This dataset, enhanced by COSMIC and supplementary GNSS-RO missions, reveals the seasonal and regional structure of PBLH, including sea ice effects near Antarctica (Ho et al., 2024). Such products are valuable for broad climatological analyses over oceans and remote regions, but their degree-scale horizontal resolution cannot resolve sharp gradients across coastlines, mountains, urban areas, or sea-ice margins. COSMIC-2 also improves sampling mainly in the tropics and subtropics, so complementary commercial RO missions and other observations remain important for higher latitudes, where recent evaluations of Spire and GeoOptics show promise for Arctic PBLH studies but still require attention to lower-tropospheric penetration and processing choices (Ganeshan et al., 2025).

Thermodynamic-profile-based PBLH retrievals complement aerosol and turbulence methods. Potential-temperature, humidity, refractivity, and inversion diagnostics from radiosondes, RL, DIAL-assisted humidity profiling, AERI, MWR, or RASS can identify thermal PBLH when the gradients are resolved, although performance depends on vertical resolution, retrieval smoothing, and inversion strength.

3. Remote sensing of boundary layer thermodynamics and turbulence

This section reviews remote sensing technologies for monitoring PBL thermodynamics. Active lidar systems, including RL and Differential

Absorption Lidar (DIAL), provide high-resolution humidity and temperature profiles and can support thermal PBLH estimates when inversion or moisture-gradient structure is resolved (Spuler et al., 2015; Goldsmith et al., 1998; Newsom et al., 2013). Passive IR and microwave sounders provide broader thermodynamic context but generally coarser vertical information near the surface. Doppler lidar is also discussed for vertical velocity and turbulent mixing. The strengths and limitations of the key technologies discussed in this section are summarized in Table 1.

3.1. Thermodynamic profiles from active lidar

PBL thermodynamics is linked to the profiles of temperature, humidity, and turbulence. Despite advances in satellite technology for moisture and temperature retrieval, these spaceborne missions face challenges in probing the lower troposphere below 2–3 km with the vertical resolution required to capture temperature inversions and thin, humid, or dry air masses (Hammann et al., 2015; Turner and Blumberg, 2018). This gap underscores the need for ground-based remote sensing techniques like RL, which can provide detailed, high-resolution profiles of humidity and temperature within the lower troposphere (Wulfmeyer et al., 2015; Su et al., 2017b).

3.1.1. Humidity profiles from Raman lidar and DIAL

Understanding humidity variability within the PBL is crucial due to its significant impact on energy balance and cloud formation. Such variability can occur at small scales, with fluctuations spanning tens of meters and minutes, and is influenced by factors such as surface heating, atmospheric mixing, and local meteorological conditions, especially in the PBL entrainment zone, where significant gradients can occur. These large fluctuations underscore the need for precise and continuous monitoring to capture the dynamics of water vapor within the PBL, for which RL systems are particularly well suited due to their capacity to deliver lower-tropospheric water vapor measurements.

Because the PBL exhibits considerable variability in water vapor, RL

systems can track the rapid evolution of humidity within it. The development of RL for atmospheric sounding dates to the 1960s, with foundational work by Cooney (1968) and Melfi (1972). It experienced a resurgence in the late 1980s thanks to advances in laser and detector technologies, marking a significant evolution in atmospheric research tools. As an example, Fig. 4 illustrates water vapor retrievals from RL, capturing the detailed vertical structure of humidity through time-height cross-sections. The figure shows that the structure of moisture layers across the atmosphere is closely associated with the PBL and reflects the capability of RL to capture fine vertical moisture structure.

The evolution of RL systems illustrates ongoing efforts to address measurement biases and errors, such as those introduced by spectral filtering and detector non-uniformities. These systematic errors, if uncorrected, can compromise the accuracy of humidity and temperature measurements (Chazette et al., 2014; Totems et al., 2019). Addressing these challenges through advanced system design and calibration techniques can enhance the reliability of RL for studying fine-scale PBL processes. The uncertainty in humidity measurements using RL varies, typically around 5% under favorable conditions like clear skies and high signal levels, whereas the uncertainty can increase to 10–20% in the presence of aerosols or thin clouds (Dai et al., 2018; Ferrare et al., 1995). Regular calibration against reference instruments, such as radiosondes, helps maintain measurement accuracy (Whiteman et al., 2006).

In addition to RL, DIAL is another lidar-based technology for retrieving humidity profiles (Browell et al., 1979; Wirth et al., 2009). DIAL operates on the principle of differential absorption by the atmosphere at two closely spaced wavelengths, where one wavelength is absorbed by water vapor and another is minimally absorbed, allowing water vapor concentration to be determined (Bösenberg, 1998). Unlike RL, which relies on large, high-peak-power ultraviolet lasers to capture small Raman scattering cross-sections and requires frequent calibration, DIAL measures a single species at a time and leverages single-frequency and frequency-agile pulsed lasers. Because DIAL uses elastic backscatter signal ratios from closely spaced wavelength pairs around a water-vapor

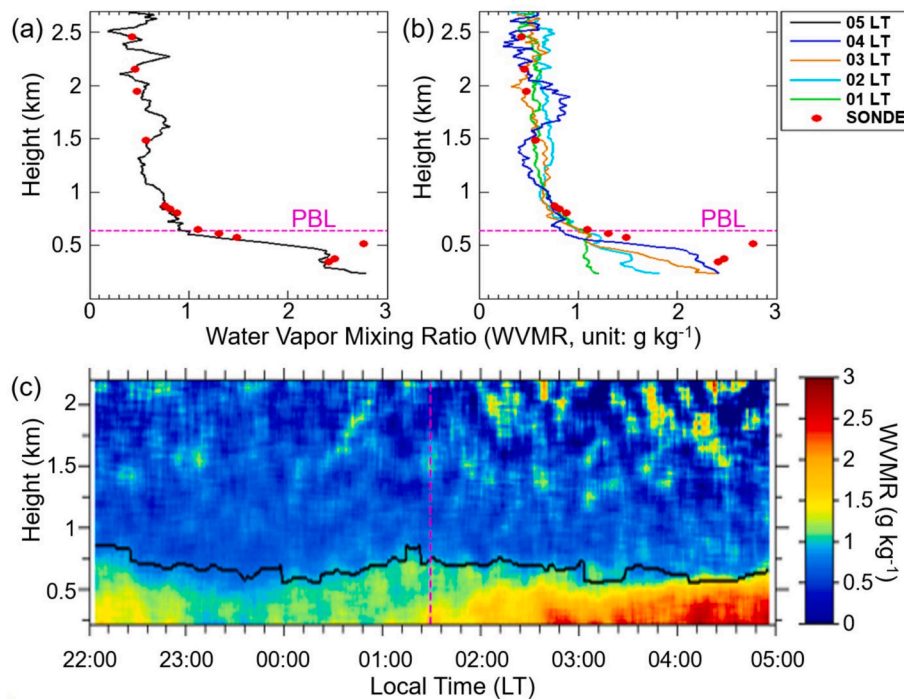


Fig. 4. (a–b) Water vapor mixing ratio (WVMR) measured by Raman lidar (RL) using the data in Su et al. (2017b). The green, light blue, brown, darker blue, and black curves indicate the nocturnal changes in the WVMR (01–05 LT) profile over Beijing, respectively. Red dots and the pink line indicate the WVMR and sonde-derived PBLH based on thermodynamic-profile interpretation. (c) Temporal changes of WVMR vertical profiles. The black line indicates the top of the residual layer, which is not necessarily the current turbulent PBL under stable nocturnal conditions. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

absorption line, it can reduce dependence on external calibration relative to RL (Ehret et al., 1993). These characteristics, along with advances in laser technology, position DIAL as a useful tool for profiling water vapor, particularly in field campaigns and long-duration deployments. This capability has also been highlighted in broader assessments of thermodynamic profiling technologies (Hardesty et al., 2012). For example, the NCAR-MSU micropulse water vapor DIAL has demonstrated unattended day-night profiling of lower-tropospheric water vapor (Spuler et al., 2015; Weckwerth et al., 2016), and OSSE work has shown that assimilating water-vapor profiles from micropulse DIAL can improve convective-weather analyses (Kay et al., 2022). DIAL performance is nevertheless sensitive to absorption-line selection, clouds, attenuation, and high-water-vapor conditions, so its uncertainty characteristics should be stated separately from those of RL.

3.1.2. Temperature profiles from Raman lidar

In addition to the water vapor variability, the acquisition of accurate temperature profiles in the lower troposphere can reveal the PBL stratification and stability, providing quantitative constraints on a key attribute of convective, neutral, or stable boundary layers. RL leverages the Raman scattering of atmospheric molecules, primarily N_2 and O_2 , which exhibit temperature-dependent backscatter signals, to produce direct retrievals of atmospheric temperature (Behrendt, 2005).

RL has become a reliable technique for atmospheric temperature measurements in the lower troposphere, offering high temporal and spatial resolution. It can achieve a vertical resolution of 10–100 m and temporal resolution ranging from seconds to a few minutes, while maintaining low biases around 1–2 K, even in the presence of aerosols and thin clouds (Behrendt et al., 2004; Di Girolamo et al., 2004). This technique has been refined to reduce measurement uncertainty by up to 70% for nighttime case studies, as demonstrated by the University of Hohenheim's lidar system (Radlach et al., 2008; Hammann et al., 2015). For PBLH applications, however, a 1–2 K temperature uncertainty must be interpreted relative to inversion strength and vertical smoothing: strong inversions can be detected reliably, whereas weak or shallow SBL inversions may remain difficult to locate.

The development and deployment of RLs have enhanced vertical temperature profiling for PBL studies (Behrendt et al., 2015; Lange et al., 2019). Despite challenges associated with daytime detection range, these advancements have led to RL systems capable of providing high-resolution temperature and humidity profiles both day and night, offering essential data for PBL thermodynamic variables (Adam et al., 2016; Wulfmeyer et al., 2015).

3.2. Thermodynamic profiles from passive sounders

Passive sounders, including hyperspectral infrared (IR) and microwave instruments, provide temperature and humidity profiles helpful for characterizing the thermodynamic structure of the PBL. Their strength lies in broad spatial coverage and continuous observations from space or ground networks, complementing active remote sensing systems. However, their relatively coarse vertical resolution (typically 1–4 km) poses challenges for accurately resolving fine-scale PBL processes.

3.2.1. Hyperspectral infrared sounders

Hyperspectral IR sounders have strengthened our ability to observe the atmosphere, providing detailed profiles of temperature and water vapor. Instruments like the Atmospheric Infrared Sounder (AIRS) on NASA's Aqua satellite, leverage high spectral resolution over a broad IR spectrum to discern the vertical structure of the atmosphere (Chahine et al., 2006). The Atmospheric Emitted Radiance Interferometer (AERI), a ground-based IR sounder, provides high-resolution atmospheric emission spectra, offering vertical information of water vapor and temperature (Feltz et al., 2003).

The process of retrieving atmospheric profiles from hyperspectral IR sounders is complex, requiring sophisticated algorithms to navigate the

ill-posed nature of the problem, where multiple atmospheric states can produce similar radiance spectra. Techniques such as optimal estimation are employed to constrain retrievals, using prior knowledge to inform solutions and produce diagnostics such as the averaging kernel matrix, which quantifies the retrieval's sensitivity to the true atmospheric state (Rodgers, 2000).

For ground-based instruments, AERI is noted for its high accuracy in measuring downwelling spectral infrared radiation, which enables continuous monitoring of the PBL (Turner and Löhnert, 2014). Combining AERI and active sensors, such as Doppler lidar, can further provide comprehensive vertical profiles of temperature, humidity, and wind within the PBL (Wagner et al., 2019). Satellite sensors, such as AIRS, extend this capability to wide regions, and geostationary (GEO) satellites offer the distinct advantage of continuous time-series observations. Advanced hyperspectral IR sounders in GEO orbits can improve spatial and temporal sampling, with a temporal resolution of 10 min and a horizontal spatial resolution of 4 km, compared to the traditional resolution of over 10 km (Adkins et al., 2021; Smith Sr et al., 2009). However, the effective vertical resolution of passive IR retrievals near the surface remains relatively coarse and is constrained by clouds, surface emissivity, prior information, and averaging kernels. Thus, AERI- or AIRS-type products are most useful for thermodynamic context and selected inversion studies, rather than as stand-alone high-resolution PBL profilers in all conditions.

3.2.2. Microwave sounders

In addition to IR sounders, microwave sounders also provide important thermodynamic information, including temperature and humidity profiles, as well as precipitable water vapor and liquid water path. The principle of microwave sounders involves measuring natural microwave radiation emitted by Earth's surface and atmosphere, which correlates with different atmospheric variables (Waters et al., 2006). Ground-based microwave radiometers (MWRs) operate on this principle, offering useful data for PBL research by capturing continuous measurements of temperature, water vapor, and liquid water in various atmospheric conditions (Crewell and Löhnert, 2007; Güldner and Spänkuch, 2001; Rose et al., 2005). Furthermore, combining MWR and active remote sensors like lidars enhances profile retrievals and reduces uncertainty (Turner and Löhnert, 2021).

Space-borne microwave sounders, such as the Advanced Technology Microwave Sounder (ATMS) on Suomi NPP, are recognized for their atmospheric profiling capabilities, particularly in measuring temperature and water vapor (Weng et al., 2013; Ferraro et al., 2005). A distinct advantage of microwave sensors is their relative all-weather capability, which allows observations through many cloud conditions and facilitates sounding of vertical temperature and water vapor profiles (Cardinali, 2009). Despite these capabilities, the existing vertical resolution of microwave sounders, typically between 2 and 4 km in the lower troposphere, presents a significant limitation for detailed PBL analysis. Achieving the vertical resolution required for comprehensive PBL studies hinges on overcoming the technical challenges associated with developing microwave sounders.

Hyperspectral microwave sensors, proposed and supported by leading space and meteorological agencies (Blackwell et al., 2010; Aires et al., 2015; Gambacorta et al., 2023), have been suggested as a possible future avenue for improving temperature and water vapor profiling. Acknowledged by NASA's PBL Incubation Study Team (Teixeira et al., 2021) as important for future PBL observations, hyperspectral microwave sensors aim to improve data assimilation by overcoming the sparse spectral coverage and limited vertical resolution of current systems. At present, however, microwave temperature and humidity retrievals still generally have insufficient vertical information to resolve many shallow PBL inversions or cloud-coupling transitions. This conclusion is consistent with broader thermodynamic profiling requirements and recent information-content and vertical-resolution studies (Hardesty et al., 2012; Wagner et al., 2019; Loveless et al.,

2022; Gambacorta et al., 2023). Therefore, this review treats hyperspectral microwave sounding as an important future direction rather than a current solution to all PBL thermodynamic profiling needs. Passive sensors are fundamentally limited for resolving shallow PBL structure due to coarse effective vertical resolution and inversion dependence, and thus are not ideal stand-alone tools for detailed PBLH retrieval.

3.3. PBL turbulence from Doppler lidar

The exploration of vertical velocity utilizing Doppler lidar technology marks a significant leap for detecting PBL turbulence. This technique provides direct observational constraints on turbulent mixing processes essential for PBL development (Garratt, 1994; Gal-Chen et al., 1992). By capturing the dynamic redistribution of momentum, mass, and humidity, Doppler lidar has refined our understanding of turbulence, a key process driven by buoyancy and wind shear (Deardorff, 1972; Tucker et al., 2009; O'Connor et al., 2010; Newsom et al., 2019; Lareau et al., 2018).

Doppler lidar's high temporal (less than 1 min) and vertical (less than 50 m) resolution enables valuable profiling of PBL turbulent activity, including both convective mixing, predominantly initiated by surface heating during the day, and shear-driven mixing, triggered by atmospheric friction and low-level jets (Gal-Chen et al., 1992; Banta et al., 2006, 2007; Tuononen et al., 2017). These mechanisms govern the vertical transport of aerosols and the exchange of heat and moisture (Fuentes et al., 2016). Although such measurements are highly useful for vertical velocity statistics and PBL evolution, one-minute averages should not be interpreted as equivalent to high-frequency in situ turbulence measurements; the relevant averaging time and scan strategy should be considered.

Advances in remote sensing technologies, particularly Doppler lidar, have substantially improved our capacity to measure radial velocities across the NBLs and CBLs, shedding light on PBL turbulent processes. Doppler lidar has been used to estimate wind turbulence parameters—such as kinetic energy, dissipation rate, integral scale of turbulence, and momentum fluxes—by analyzing the radial velocity within the inertial subrange of turbulence (Banakh and Smalikho, 2013). Innovations in methodology, such as those presented by Harvey et al. (2013), introduce an advanced classification of turbulence sources within the PBL using Doppler lidar data. Behrendt et al. (2020) provide the first measurements of sensible heat flux profiles in the daytime CBL using combined temperature rotational RL and Doppler lidar over western Germany.

4. Remote sensing of boundary layer clouds

This section focuses on the remote sensing of characteristics of BLCs through advanced remote sensing technologies. As a part of the PBL system, BLCs, including shallow cumulus and stratiform types, exhibit considerable vertical variability in thermodynamic properties, complicating their analysis and necessitating development of specialized remote sensing techniques. This section discusses remote sensing techniques and their applications for detecting cloud occurrence, fraction, and updrafts; these directly impact PBL processes by influencing heat and moisture transport, cloud formation, and dissipation. Although remote sensing of cloud microphysics is another significant and broad area of study, it is not the primary focus of this section.

4.1. Active remote sensing of boundary layer clouds

Remote sensing of BLC occurrence and fraction presents both challenges and opportunities for understanding atmospheric processes and validating atmospheric models. Active remote sensing technologies, such as lidar and radar, play a crucial role in accurately capturing vertical profiles of clouds. The integration of these technologies provides

comprehensive data that help overcome the limitations of individual instruments (Spinhirne, 1993; Moran et al., 1998).

Active remote sensing of BLCs is primarily conducted using lidars, ceilometers, cloud radars, and MWRs. Lidar and ceilometers utilize laser beams to determine cloud bases by timing the return of reflected signals. Lidars, equipped with low-pulse energy lasers, can detect thin clouds and smaller atmospheric particles (Campbell et al., 2002; Liu et al., 2014; Zhao et al., 2014; Chu et al., 2022). Ceilometers measure the same parameters but typically operate at lower power and are optimized for routine, autonomous operation over extended periods. Their reported maximum range varies by model and configuration; for example, several widely used operational ceilometers have maximum ranges of only several kilometers, and the useful PBL retrieval range of these instruments is often much lower because it depends on SNR and overlap. Millimeter-wave cloud radars (MMCR), operating at 35 GHz (Ka-band), penetrate through cloud layers to reveal detailed vertical structures (Clothiaux et al., 1999; Verlinde et al., 2013). Complementarily, MWRs measure integrated liquid water path within clouds, a key parameter for cloud microphysics and cloud-remote-sensing applications (Turner, 2007). In practice, multi-instrument approaches such as ARM-style combinations of lidar, radar, ceilometer, and MWR observations provide a more robust cloud-boundary and cloud-liquid-water context than any single sensor alone (Illingworth et al., 2019; Kollias et al., 2020).

Various methods and algorithms are employed across different instruments to detect clouds, each optimized for specific atmospheric characteristics. For lidars or ceilometers, algorithms typically rely on distinguishing the lidar signal from the background ambient light signal (Pal et al., 1992). This differentiation is done by using a threshold method, which detects clouds when the lidar return significantly exceeds the background signal (Wang and Sassen, 2001). Techniques like log-scale linear interpolation measure the layer signal intensity related to molecular scattering, adjusting for cloud attenuation effects (Campbell et al., 2008). MMCR employs radar waves to penetrate cloud layers and detect the internal structure and vertical extent of clouds. MMCR algorithms are designed to handle complex signal processing, differentiating between hydrometeors and other particulates such as insects or dust (Moran et al., 1998). Multi-sensor work by Wang and Sassen (2001) showed that combined lidar, millimeter-wave radar, infrared radiometer, and microwave radiometer observations can support cloud-type classification and cloud macrophysical-property retrieval.

These remote sensing technologies, such as laser ceilometers, MPL, and cloud radar, each offer distinct advantages for capturing vertical profiles of clouds. Laser ceilometers and MPL are highly effective in detecting cloud base heights with a high degree of accuracy, typically exhibiting biases of less than 0.1 km, and provide rapid measurements with temporal resolutions ranging from less than 10 s to about one minute. However, their signals are quickly attenuated by optically thick clouds, limiting their ability to penetrate multiple cloud layers. On the other hand, cloud radars penetrate clouds and reveal detailed vertical structures, making them essential for observing higher cloud layers when lower layers are present. However, cloud radar can be affected by large precipitation particles and non-hydrometeor particulates, such as insects and pollen, which can complicate cloud-base height estimation. MWR complements these instruments by measuring the integrated liquid water path in clouds, providing valuable data during periods of heavier precipitation when laser retrievals often fail.

The ARM program exemplifies the integration of various remote sensing technologies at sites worldwide, utilizing instruments such as the Belfort and Vaisala laser ceilometers, MPL, MMCR, the Ka-band ARM Zenith Radar, and MWR (Clothiaux et al., 2000; Kollias et al., 2020). This integrated approach combines the capabilities of lidars and ceilometers for detecting cloud bases and thin clouds, cloud radar penetration of multiple cloud layers, and MWR liquid water path information. This synergistic approach enhances the robustness of cloud masks and is particularly useful for capturing the diurnal cycle of BLCs.

Beyond occurrence and fraction, active remote sensing has also advanced the characterization of cloud-PBL coupling, which strongly influences BLC evolution. Coupled clouds occur when surface-driven turbulence extends to the cloud base, linking surface fluxes, the PBL, and cloud development, whereas decoupled clouds form above the entrainment zone and respond less directly to surface forcing, as illustrated in Fig. 5 (Bretherton and Wyant, 1997; Su et al., 2022). Fig. 5 is intended as a schematic illustration of coupling states; the indicated PBLH should not be interpreted as an exactly measured level within the entrainment zone. Lidar-derived PBLH, combined with diagnostics such as the LCL and radiosonde thermodynamic profiles, can provide a practical way to classify coupling state, but uncertainties remain when cloud layers are multilayered or when the PBLH definition differs among instruments.

Identifying BLCs based on active remote sensing of clouds is important for understanding PBL processes. As a representative type of BLCs, shallow cumulus (ShCu) can form at the entrainment zone at the top of the PBL and are associated with fair weather conditions. These clouds develop from boundary layer updrafts that reach the LCL, with their bases exhibiting minor variations due to local differences in updraft water vapor (Crum and Stull, 1987). ShCu can be classified into active and forced types based on their depth and dynamics (Stull, 1988). Active ShCu, which are deeper, generate their own buoyant ascent after reaching the level of free convection, whereas forced ShCu are shallower and serve as tracers of boundary layer updrafts (Zhang and Klein, 2013; Lamer and Kollias, 2015). The presence of ShCu influences CBL processes, including virtual heat flux profiles and vertical velocity variance (Nicholls and Lemone, 1980; Hogan et al., 2009). Techniques for differentiating ShCu from other cloud types in cloud masks generated by active remote sensing technologies using scientific understanding and derived criteria have been developed (Zhang and Klein, 2010, 2013; Lareau et al., 2018; Berg and Kassianov, 2008). In addition to the detection of ShCu, Su et al. (2023) differentiated stratiform clouds among BLCs based on objective criteria of overcast clouds and continuous coverage.

Active remote sensing of BLCs enhances the evaluation of these

clouds in atmospheric models by providing detailed observations necessary for understanding the model's limitations. For example, remote-sensing-based observations that capture the diurnal cycle of ShCu, including their life cycle and response to surface conditions, are essential for improving model parameterizations and reducing biases in climate predictions (Berg et al., 2013; Tao et al., 2019; Chen et al., 2020; Tian et al., 2022). To address this issue, advances in ground-based instruments, like scanning cloud radars and stereo cameras (Romps and Öktem, 2018), have improved the detection and characterization of ShCu by overcoming the limitations of traditional zenith-pointing radars and lidars, such as signal attenuation and ground clutter. Different scanning strategies (e.g., PPI and RHI) and collocation with other profiling instruments further extend their three-dimensional sampling of cloud and boundary-layer structure (Kollias et al., 2020). These technologies enable more accurate studies of cloud morphologies, cloud life cycles and their interactions with the PBL, although challenges remain in detecting thin, low-reflectivity clouds (Kollias et al., 2020). These remote sensing technologies facilitate direct comparison and evaluation of cloud characteristics within both large-eddy simulations and climate models (Zhang et al., 2017; Fast et al., 2019; Tao et al., 2021). Fig. 6 illustrates the comparison of ShCu from active remote sensing and large-eddy simulations, and demonstrates both similar patterns and differences in the vertical extent, as well as the magnitude of cloud fraction. By leveraging active remote sensing data, researchers can capture the diurnal cycle of BLCs, helping to bridge the gap between observations and models.

4.2. Satellite detection of boundary layer clouds

The detection of BLCs, including ShCu and stratiform clouds, has a long tradition in satellite meteorology (Goren et al., 2018; Cesana et al., 2019). Satellite observations frequently provide information on cloud fraction, location, and occurrence over large areas, contributing to studies on the evolution of BLCs (Rodts et al., 2003; Romps and Vogelmann, 2017). For example, the Visible Infrared Imaging Radiometer Suite (VIIRS) and Landsat instruments onboard polar-orbiting

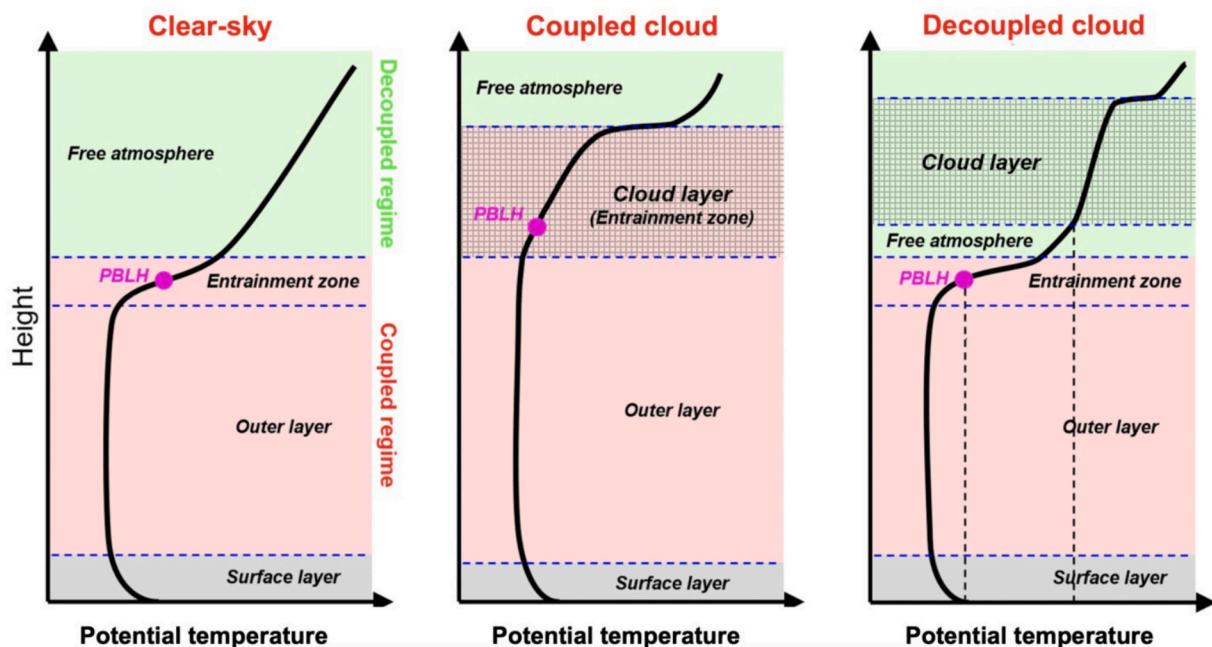


Fig. 5. Idealized vertical profiles of potential temperature under clear-sky, coupled, and decoupled cloud conditions over land. Gray and red shading denote the near-surface and mixed layers, respectively, with the entrainment zone above and the free atmosphere (green) aloft. Cross-hatching indicates the cloudy layer position relative to the PBL entrainment zone, and pink dots mark the PBLH schematically. The figure is conceptual and does not imply exact determination of PBLH within the entrainment zone. Adapted from Su et al. (2022). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

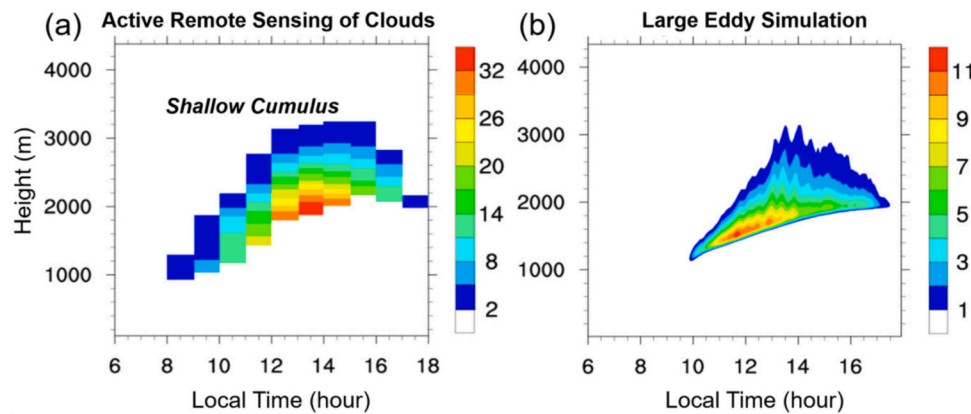


Fig. 6. Diurnal cycle of vertical cloud fraction (%) for shallow cumulus based on (a) active remote sensing of clouds (radar-lidar-ceilometer combined value-added data) and (b) large-eddy simulation. The colour bar ranges differ between observations and simulations to optimize dynamic range in each panel. The data are derived from the Continental Active Surface-Forced Shallow Cumulus composite case detailed in Zhang et al. (2017), based on ARM Southern Great Plains observations and corresponding large-eddy simulations, illustrating how active remote sensing constrains model representation of cloud timing, depth, and vertical distribution.

satellites offer such coverage, though they are limited in capturing diurnal variations of BLCs because they are in sun-locked orbits that observe all locations at roughly the same time-of-day (Chambers et al., 1997). Geostationary satellites, such as the GOES-R Series, enhance cloud detection capabilities with instruments like the Advanced Baseline Imager (ABI), which provides high temporal (~10 min) and spatial (0.5–2 km) resolution data, depending on the spectral channel, thereby enabling continuous monitoring of ShCu and other cloud types over large regions (Schmit et al., 2017; Tian et al., 2021, 2024).

These satellite observations have been applied to analyze how BLCs interact with the surface energy budget and fluxes at various scales. Different surface cover types, such as vegetation and urban areas, exhibit distinct physical properties that influence heat fluxes between the surface and the PBL, impacting cloud development and spatial patterns (Collier, 2006; Borg and Bennartz, 2007; Tao et al., 2019, 2021). Satellite observations of BLCs provide the basis for improving the understanding of these interactions by comparing cloud fractions and their spatial anomalies across different land cover types (Teuling et al., 2017; Theeuwes et al., 2019). Studies have shown that urban heat islands can enhance afternoon cloud cover during the warm season (Theeuwes et al., 2019; Vo et al., 2023).

Advances in passive satellite sensors have laid the foundation for the detection of BLCs, especially for the detection and analysis of cloud top properties. As outlined by Hillger et al. (2013), VIIRS offers detailed, high-resolution imagery that can be used for identifying cloud top properties, such as cloud-top height and cloud-top temperature, as well as cloud droplet size. This capability is particularly beneficial for studying single-layer low clouds, where VIIRS's spectral, spatial, and temporal resolutions provide cloud-top properties for understanding cloud evolution. Thus, passive satellite sensors can be used to capture and analyze the characteristics of BLCs for the single-layer clouds, as well as their interactions with other environmental conditions (Tian et al., 2022; Kubar et al., 2011). However, the effectiveness of multi-spectral imagery may be limited in capturing the full complexity of multi-layer cloud systems.

In addition to passive remote sensing, active remote sensing instruments can improve the classification of cloud types (Stephens et al., 2002; Winker et al., 2010). CloudSat's CPR, with its cloud penetration capabilities, retrieved cloud vertical structure from 2006 to 2023. CloudSat results have facilitated examination of cloud overlap suitable for model parameterization (Shonk et al., 2010; Oreopoulos et al., 2012), the impact of cloud systems on atmospheric radiative profiles (Oreopoulos et al., 2017), and the alignment of passive and active cloud observations (Mace and Wrenn, 2013; Leinonen et al., 2016). Despite

these advances, CloudSat faced limitations due to its spatial coverage and diminished sensitivity to heavy precipitation (Stephens et al., 2002). Validation against CloudSat observations, as conducted by Seaman et al. (2017), revealed that shallow or optically thin clouds, as well as small-scale cumulus, were often missed or inadequately captured, underscoring the challenges inherent in satellite-based cloud detection. The performance discussions surrounding CloudSat's CPR, especially its detection capabilities of marine BLCs (Christensen et al., 2013; Rapp et al., 2013), further highlight these observational gaps. Satellite cloud observations alone generally do not establish whether a cloud lies within the boundary layer. In practice, satellites distinguish BLCs from clouds above the PBL by combining cloud-top or cloud-base information with PBLH, LCL, vertical cloud structure from active lidar sensors such as CALIOP/CALIPSO (Winker et al., 2009), thermodynamic profiles, or reanalysis context; passive imagery alone is often insufficient for this classification. Thermal-IR methods constrained by reanalysis temperature profiles can also help infer the height of elevated features such as smoke plumes (Lyapustin et al., 2020), and multi-angle imagery such as MISR can provide additional cloud-height constraints (Diner et al., 1998). These height constraints are useful context for cloud classification but do not by themselves identify the PBL top.

The combination of lidar, radar, and satellite technologies has improved our capability to monitor BLCs. By integrating ground-based and satellite observations, the remote sensing techniques provide insights into cloud fractions, lifecycles, and their impact on climate models (e.g., Dong et al., 2002; Tao et al., 2021; Neggers et al., 2003; Mace and Wrenn, 2013).

4.3. Remote sensing of sub-cloud updraft

This section discusses the remote sensing of cloud-base updraft velocity from ground-based Doppler lidar and satellites. Despite the critical impact of cloud-base updraft velocity on cumulus cloud microphysics and the entrainment process, its explicit representation remains largely absent in conventional cumulus parameterization schemes, which often rely on cloud-base mass flux without direct reference to cloud-base updraft speed (e.g., Arakawa and Schubert, 1974). Some parameterizations do provide vertical velocities (e.g., Bretherton et al., 2004; Donner et al., 2011), but their realism has received limited evaluations, in part due to the scarcity of observational constraints. This poses a barrier to accurately simulating essential cloud processes and their interaction with aerosols (Donner et al., 2016; Rosenfeld et al., 2014; Lareau et al., 2018).

The advent of ground-based Doppler lidar technology has helped

bridge this observational gap by providing retrievals of vertical velocities in the sub-cloud layer. Vertical velocity is obtained from Doppler lidar and radar measurements that capture the motion of particles within the cloud or aerosol layer. Lhermitte (1987) introduced a 94-GHz Doppler radar for observing clouds and precipitation, highlighting its capability to measure Doppler velocity. Several studies advanced these technologies to derive vertical velocity profiles, contributing to our understanding of the dynamics of BLCs (Kollias et al., 2001; Ansmann et al., 2010). Doppler lidar has enabled detailed observations of updrafts and downdrafts, providing useful information on the development of convective processes across various terrains and atmospheric conditions. Doppler lidar can observe diurnal cycles of the PBL and capture turbulent mixing, including the entrainment zone (Lothon et al., 2006; Gibert et al., 2007; Hogan et al., 2009). These observations are valuable for improving our understanding of organized convection within the PBL and for enhancing vertical flux schemes in atmospheric models.

The interaction between boundary-layer cumulus clouds and the thermals that initiate them is crucial not only for the turbulence structure of the CBL but also for understanding the venting of pollutants and the triggering of deep moist convection (Kollias et al., 2001; Donner and Phillips, 2003). By characterizing the statistics of updrafts and downdrafts, Doppler lidar has advanced the understanding of boundary layer dynamics and improved cloud parameterizations in atmospheric models (Jakob and Siebesma, 2003; Verzijlbergh et al., 2009).

Despite the potential of Doppler lidar and other in-situ measurement techniques, the scarcity of observations and the limited spatial coverage of traditional methods underscore the urgency of developing new methodologies for cloud-base updraft estimation. To address this limitation, satellite remote sensing has emerged as an important tool for observing cloud-base updraft velocity. Recognizing these limitations, a series of studies have explored the use of satellite data to infer cloud-base updraft across extensive areas, enhancing our understanding of cloud evolution under certain circumstances. For example, methodologies developed by Zheng et al. (2015) and Zheng and Rosenfeld (2015) leverage satellite observations, such as VIIRS onboard the Suomi NPP, to estimate cloud-base updraft speed of boundary layer convective clouds by relating it to surface and boundary layer physical parameters that are retrievable from these satellite instruments (Fig. 7a). The methodologies underscore the dominant control of surface heating on convective

updrafts that form and sustain clouds over the continent. This concept is extended by Zheng et al. (2016) and Zheng (2018) to marine stratocumulus clouds, where the updrafts are predominantly propelled by cloud top radiative cooling rather than surface heating. By calculating the cloud top radiative cooling from satellite-retrieved cloud parameters along with reanalysis soundings (Zheng et al., 2019), one can infer the updraft speed (Fig. 7b). This shift in focus from convective to stratiform cloud regimes broadens the applicability of satellite-based updraft retrievals to a cloud regime central to climate feedbacks and marine cloud brightening research.

Despite the advantages, challenges persist. For instance, satellite-based estimations of cloud-base updrafts hinge on establishing relationships between updrafts and boundary layer energetics. Theoretical derivations of these relationships are based on assumptions such as uniform boundary layer thermodynamics and idealized cloud geometry, thereby introducing some uncertainties and restricting their universal applicability (e.g., Zheng et al., 2015, 2018, 2020b; Zheng, 2019). Moreover, the sparse ground observations of updrafts impede comprehensive evaluation of the satellite estimates against the 'ground truth'. Large field campaigns such as IHOP_2002 and PECAN illustrate the value of coordinated water-vapor, wind, cloud, and thermodynamic profiling for convective initiation and nocturnal convection studies (Weckwerth et al., 2004; Geerts et al., 2017). As such, acquiring accurate datasets on cloud-base updraft is important for advancing our understanding of cloud lifecycle, aerosol-cloud interactions (Fan et al., 2016; Li et al., 2017b; Rosenfeld et al., 2019) and their broader climatic impacts (Donner et al., 2016; Seinfeld et al., 2016).

5. Challenges and perspectives

Building on the previous sections that highlighted the strengths of ground-based and satellite remote sensing techniques for monitoring PBLH, thermodynamics, and BLCs, this section focuses on their limitations, uncertainties, and future directions. It summarizes key challenges that affect their application and outlines future opportunities for improving PBL observations through multi-source data fusion and artificial intelligence.

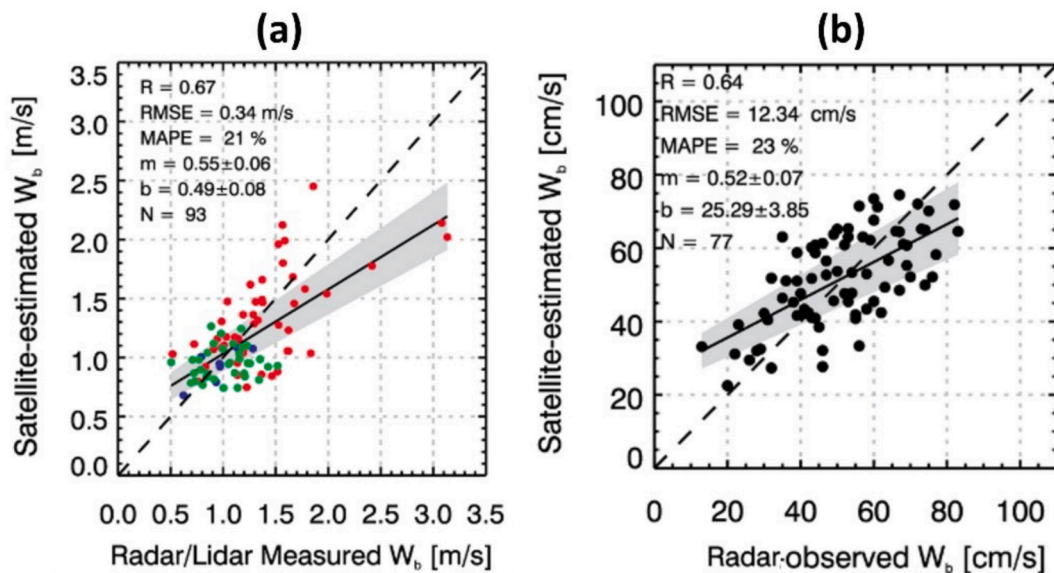


Fig. 7. Validation of satellite-estimated cloud-base updraft velocity, W_b , against ARM ground observations from Doppler radar and lidar for (a) convective clouds over the Southern Great Plains (red), eastern Pacific (blue), and Amazon region (green), and for (b) stratocumulus clouds over the eastern Pacific. Summary statistics (R , $RMSE$, $MAPE$, m , b , and N) are shown. Based on data from Zheng and Rosenfeld (2015) and Zheng (2018). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

5.1. Limitations and challenges

5.1.1. Ground-based instruments

Ground-based instruments for PBL and BLC studies, such as ceilometers, MPL, RL, Doppler lidar, cloud radar, and RWP, are summarized with their strengths and limitations in Table 1. Although these instruments provide high-resolution vertical profiles of temperature, humidity, and wind, their utility is constrained by several factors, including limited spatial representativeness over complex surfaces such as cities, mountains, coastlines, marine environments, and polar ice or snow surfaces. This limitation restricts the ability to capture the spatial variability of the PBL across larger geographic areas, making it challenging to integrate them into global atmospheric models.

The calibration and maintenance of ground-based instruments also present challenges. Ensuring the long-term stability and accuracy of these systems, such as lidars and MWR, requires regular calibration against reference measurements, which can be resource-intensive. Moreover, environmental factors such as temperature and humidity fluctuations, and instrument aging can affect the performance and reliability of the measurements.

The application of lidar systems and AERI faces limitations in adverse atmospheric conditions such as fog and precipitation, which can largely obscure their signals or retrievals (Baars et al., 2008; Emeis et al., 2008). This is particularly problematic for studying cloud evolution and PBL processes associated with convective systems, where precipitation plays an important role in the development of convection. MWR can partly mitigate these limitations because microwave observations are less affected by nonprecipitating clouds, making them useful for continuous thermodynamic monitoring. However, MWR retrievals have relatively coarse vertical resolution and can be affected by calibration uncertainty, precipitation, and radome wetting.

For lidar systems, one notable issue is the presence of a blind zone, typically around 0.15–0.3 km, which can lead to the misidentification of a residual PBL as the current PBLH if the actual PBLH falls below this zone. Moreover, although lidar technologies are reliable during CBLs, where the aerosols and humidity are relatively well-mixed, lidar systems face challenges in accurately detecting PBLH under SBL or multiple aerosol layer conditions (Su et al., 2020; Zhang et al., 2022). Furthermore, in SBL conditions, the aerosol layer may become decoupled from the underlying thermodynamics and surface forcing, leading to discrepancies between aerosol-layer-based PBLH measurements and those derived from thermodynamic profiles.

Daytime operation poses a challenge for RL. The presence of sunlight can significantly reduce the SNR, affecting the instruments' ability to detect aerosols and clouds against the background light. This limits the detection range for RL, which relies on sampling weak Raman-scattered light, making accurate daytime measurements of temperature and humidity profiles more challenging.

When utilizing Doppler lidars, the detection range depends on the strength of radiation signals backscattered by aerosol particles. Because aerosol concentrations are often low above the boundary layer, wind retrievals above the PBL can be challenging for these systems, particularly under clean atmospheric conditions. In pristine sky conditions, such as after a rain event, the return signal may be too weak for aerosol-based Doppler lidars to provide reliable wind or turbulence retrievals. By contrast, molecular-channel Doppler lidar systems can use molecular backscatter for wind profiling in cleaner atmospheric layers (Gentry et al., 2000).

For deriving PBLH, the definition varies with measurement technique and retrieval algorithm approach. Instruments such as RL, Doppler lidar, MPL, and RWP derive PBLH with different definitions and detection principles, requiring care in interpretation. Applying PBLH products tailored to specific scenarios can help address these issues. For instance, elastic lidar systems detect material or aerosol PBLH based on aerosol layers and may be distorted by residual or multiple aerosol layers. Doppler lidar provides information on turbulence, which

is especially useful for dynamical PBLH under convective conditions but suffers from limitations in stable conditions and low SNR. Thermodynamic profiling from radiosondes, RL, DIAL-assisted humidity structure, AERI, MWR, or RASS can support thermal PBLH estimates based on inversions or stability transitions, but these estimates can be smoothed by retrieval resolution or prior constraints. RWP provide continuous PBLH estimates but are limited by lower measurement heights and sensitivity to various sources of noise, such as particles, hydrometeors, and insects.

The diverse detection strategies and definitions used by these instruments highlight the need for an integrated approach, where the strengths of one method can complement the limitations of another, thereby enhancing the accuracy of PBL characterization. Furthermore, the development of new instrument technologies and data processing algorithms continues to improve the accuracy, resolution, and operational capabilities of ground-based atmospheric observations.

5.1.2. Satellite sensors

Satellite sensors offer global coverage and long-term datasets critical for PBL climatology. However, their applications often face greater limitations and uncertainties compared to ground-based counterparts, primarily due to constraints related to satellite orbits (which affect spatial and temporal coverage), payload capacity, for some applications horizontal and/or vertical spatial resolution, and, for active sensors, power availability. These constraints affect both the accuracy and the applicability of satellite observations in PBL studies. Yet, most satellite instruments have the advantage of broad coverage and radiometric stability, which makes it possible for them to provide consistent, long-term data records required to create regional and global-scale climatologies. Table 2 summarizes the capabilities and limitations of different satellite sensors; the representative product uncertainties should be interpreted as literature-based ranges rather than uniform accuracies under all observing conditions.

One of the primary limitations of satellite sensors is their spatial and temporal resolution. IR and microwave sounders often have kilometer-scale vertical resolution and tens of kilometers in horizontal resolution, which are not adequate to resolve small-scale PBL structure. Moreover, the retrieval of accurate atmospheric profiles faces challenges due to the ill-posed nature of inverse problems and the need for prior constraints in retrieval algorithms. These limitations are especially important for shallow marine, stable, or polar boundary layers, where sharp gradients can occur close to the surface.

Bias and accuracy in satellite sensor measurements can also pose significant challenges. Factors that affect atmospheric measurements from nearly all surface as well as space-based instruments, such as sensor calibration, algorithm assumptions, and the complex nature of atmospheric processes contribute to uncertainties in data products. For example, hyperspectral IR sounders are generally less effective under optically thick clouds, leading to biases and reduced sensitivity in thermodynamic profiles within the PBL. Similarly, the accuracy of GNSS-RO measurements can be affected by ducting effects and the limited resolution in capturing the sharp gradients within the PBL.

Space-borne lidar and radar systems (e.g., CALIPSO and CloudSat) provide data only for the areas directly beneath their tracks. This limitation is compounded by challenges such as attenuation from heavy precipitation or dense cloud layers, which can significantly reduce their ability to observe PBL structures and features. For PBLH retrieval, challenges include screening residual layers and distinguishing multi-layer aerosol structures. The long travel distance of the lidar return signal also lowers the SNR compared to ground-based instruments that can more easily detect near-surface features. Operating lidars during daylight hours, especially over high-albedo icy regions, can also be challenging due to heightened solar background; in Antarctic settings, optically thin clouds and blowing snow further complicate interpretation of near-surface cloud and aerosol features (Ganeshan et al., 2022).

Moreover, remote sensing of cloud updrafts from satellite

measurements (e.g., VIIRS), though promising in principle, remains uncertain and not yet practically feasible for all scenarios. Current methodologies infer cloud-base updrafts from surface and boundary layer variables retrievable from satellites. These estimations are based upon theoretical relationships between updrafts and boundary layer energetics, which are only valid for coupled BLCs. In addition, limited spatial coverage of ground observations of updrafts prevents comprehensive evaluations against the “ground truth.” Thus, acquiring accurate datasets on cloud-base updraft remains a significant barrier to advancing our understanding of BLCs and warrants continued development in this area.

Efforts to improve satellite sensor technology, enhance data processing algorithms, and foster synergy between satellite and ground-based observations can help overcome current limitations and unlock the full potential of satellite remote sensing in PBL studies.

5.2. Future perspective

5.2.1. Multi-source data fusion

Traditional remote sensing methods, while important, often provide isolated snapshots of the PBL, limiting our ability to capture a comprehensive view that includes PBLH, thermodynamics, and BLCs. Simultaneous retrieval of these characteristics, particularly for coupled systems where clouds and PBL thermodynamics co-evolve, is essential. Accurately capturing these interactions requires an integrated, multi-source approach to achieve an integral observation of the complex PBL system, encompassing more than just its height.

Integrating remote sensing data from satellites with ground-based observations provides a comprehensive approach to characterizing different PBL aspects, including PBLH, thermodynamics, and BLCs. Detailed, localized surface-based measurements can be used to help improve the interpretation of less detailed but much more widespread satellite observations. The complexity and variability of the PBL, compounded by the transient nature of BLC formations, necessitate the fusion of data from multiple sources to obtain a comprehensive view of PBL evolution. Combining satellite observations of cloud-top properties with ground-based measurements of cloud-base characteristics, along with integrating observations of PBL thermodynamics and turbulence, exemplifies multi-source data fusion approaches. This synergy allows for detailed vertical profiling from ground-based lidar and radar while leveraging the extensive spatial coverage provided by satellite instruments. The multi-source data fusion addresses the limitations of individual data sources by jointly obtaining PBLH, vertical thermodynamic information, and BLC characteristics, thereby capturing the integral dynamics of the PBL system and its processes. The GEWEX Land–Atmosphere Feedback Observatory (GLAFO) is one such coordinated effort, combining scanning and vertically pointing lidars, radars, and radiometers to resolve boundary-layer structure (Späth et al., 2023). However, such integration poses challenges in terms of data compatibility, spatial and temporal scales, and the calibration and validation of satellite products against ground-based observations.

Advancing PBL research requires integrating remote sensing tools to capture coupled interactions among BLCs, PBL dynamics, and land surface processes (Li et al., 2017a; Su et al., 2024a). BLCs influence PBL development by modifying the radiation budget, while PBLH strongly regulates BLC evolution. Thus, joint measurements of PBLH, thermodynamics, and BLCs are essential for a comprehensive understanding of these interactions. Several studies have demonstrated simultaneous observation of PBLH, PBL turbulence, and BLCs using multiple remote sensing measurements to study PBL processes (Tian et al., 2022; Su et al., 2024b). However, these studies remain limited in spatial coverage, highlighting the need for further development of sensor techniques and algorithms to enhance the integration of key PBL parameters, as well as greater efforts to synthesize already existing data from multiple sources.

Theoretical studies of cloud-PBL-surface coupling further motivate the development and advancement of remote sensing technologies for

the PBL. These studies emphasize the importance of capturing cloud-PBL-surface coupling, where surface-originating turbulence reaches the cloud base, impacting cloud evolution. Accurate measurement of this coupling requires integrating data on PBLH, thermodynamics, and cloud base characteristics, which can be facilitated by the combined use of ground-based and satellite remote sensing tools. PBL turbulence provides direct evidence for the turbulent coupling between cloud and surface. Thermodynamic measurements, such as temperature inversions in the sub-cloud layer, serve as key indicators of cloud coupling states. Meanwhile, relative positions between PBLH, LCL, and cloud base give practical criteria for identifying cloud coupling. Consequently, the development of comprehensive remote sensing approaches is motivated by the need to understand these complex interactions.

Despite recent advancements in classifying clouds into coupled or decoupled states using MPL and radiosonde data (Su et al., 2022), current studies still face challenges in obtaining detailed information on cloud-surface coupling over wide regions. This underscores the importance of multi-source data fusion, which integrates satellite sensors, particularly space-borne lidar and radar (e.g., CALIPSO and CloudSat), with ground-based observations to enhance our capabilities for globally monitoring cloud-surface coupling. The complementary strengths of space-borne lidar in determining vertical profiles of aerosol backscatters and space-borne radar profiling of cloud structures promise a new paradigm in assessing cloud-PBL-land interactions over large regions by offering fused information on PBL and BLCs. Similar fusion is needed over oceans, remote land, and polar regions, where fixed surface-based networks are sparse and satellite sampling must be interpreted with ship, aircraft, field-campaign, or reanalysis context. This synergy could advance our understanding of the spatial and temporal evolution of cloud-surface coupling, making the integration of these diverse data sources essential for studying interactions between BLCs, the PBL, and the land surface.

5.2.2. Advancing PBL remote sensing with artificial intelligence

With the rapid development of artificial intelligence techniques, machine learning (ML) offers transformative solutions to the complexities of atmospheric sciences (Dueben et al., 2022; Kadow et al., 2020). With the ability to analyze vast datasets, these technologies can identify patterns and extract meaningful insights from the integration of multi-source data, offering strong potential for atmospheric applications and PBL estimation (Reichstein et al., 2019; Su and Zhang, 2024).

Significant progress has been made in using AI/ML to refine the estimation of PBLH, addressing the inherent complexity and variability of the PBL (Guo et al., 2024). Studies have employed ML to identify PBLH using thermodynamic profiles or backscatter profiles from lidar (Sleeman et al., 2020; Rieutord et al., 2021) or AERI (Ye et al., 2021). ML-derived PBLH retrievals can outperform conventional techniques in some scenarios, but their performance depends on training data, input features, and the representativeness of the validation cases (Krishnamurthy et al., 2021). In addition, Y. Li et al. (2023) demonstrated an ML algorithm that uses the vertical distribution of aerosols to determine PBLH under complex atmospheric conditions. Recent work has also explored ML for improving lower-tropospheric thermodynamic profiles from passive sounders (Milstein et al., 2023) and for denoising or classifying spaceborne lidar features. Meanwhile, to overcome the low SNR ratio of spaceborne lidars, new approaches such as convolutional neural networks (Palm et al., 2021) have been adopted for spaceborne lidar backscatter, showing promise for PBLH retrievals. Implementing ML approaches such as image denoising techniques could also improve the SNR of spaceborne lidars (Selmer et al., 2024). These studies highlight the potential of ML to improve PBLH retrievals and to identify additional PBL characteristics such as layer stability and turbulence intensity (de Arruda Moreira et al., 2022; Wang et al., 2019).

Furthermore, ML can support the fusion of PBL datasets from various sources, such as ground-based instruments, satellites, and in situ measurements. This approach can provide a more complete view of the PBL

and associated cloud evolution by integrating multiple remote sensing datasets. Su and Zhang (2024) exemplify this by developing a deep neural network to estimate PBLH using conventional meteorological data, trained from multiple sources of remote sensing data, demonstrating the integration of diverse datasets for more accurate PBL analysis. These applications depend on the quality and scope of the training data; as such, careful consideration of possible input-data biases, representativeness, and environmental sampling limitations is needed to ensure physically meaningful results.

6. Concluding remarks

In summary, this review highlights substantial progress in remote sensing of the PBL, from ground-based innovations to satellite observations. The discussion of PBL height, thermodynamics, and boundary layer clouds (BLCs) underscores their critical roles in atmospheric convection, weather patterns, and air quality, while also revealing the complex challenges in accurately measuring these elements. As we continue to refine parameterizations and explore the climatic implications of PBL processes, integrating advanced remote sensing technologies with theoretical models is necessary for advancing the understanding and monitoring of the PBL.

Ground-based instruments, including various types of lidars (micropulse, Doppler, Raman), ceilometers, Radar Wind Profilers (RWPs), and cloud radars, provide high-resolution and continuous vertical profiles vital for understanding PBL dynamics. However, their limitations in spatial coverage and sensitivity under certain conditions, such as heavy precipitation or SBL, underscore the need for complementary satellite observations. Satellite sensors, including hyperspectral infrared and microwave sounders, GNSS radio occultation, and spaceborne lidars and radars, offer extensive global coverage and valuable data on PBL characteristics. Yet, challenges such as relatively low spatial and temporal resolution in most cases, biases under cloudy conditions, and the complexity of interpreting multilayer cloud structures highlight the necessity for further advancements and integration with ground-based measurements.

The synthesis of data from ground-based instruments, satellites, and in situ measurements, coupled with advancements in ML, offers a promising path forward. These technologies have the potential to reduce gaps in current understanding by integrating multi-source data into a more complete view of the PBL. In particular, the simultaneous retrieval of PBL characteristics and coupled BLCs presents an opportunity to capture the evolution of these atmospheric phenomena. The application of ML in processing and analyzing integrated data can help mitigate traditional limitations and provide new insights into PBL processes and cloud interactions.

In conclusion, although significant progress has been made in remote sensing technologies, continued innovation and integration across platforms are essential for overcoming current limitations. By leveraging advancements in ML, along with the synergy of ground-based and satellite observations, the scientific community can enhance its ability to monitor and model the PBL processes more accurately. The journey towards a comprehensive understanding of the PBL, the region of the atmosphere most directly relevant to habitability, and its impact on our climate and weather systems is far from complete, but with the collaborative efforts of the scientific community, supported by innovative technologies (e.g., future satellite mission concepts and observing-system efforts), we are closer than ever to achieving this goal. As we move forward, the insights gained from this review can serve as a reference for future development of instruments, scientific exploration, and strategic planning in addressing the challenges posed by the complex PBL processes. These efforts can contribute to a better understanding of the PBL system and its impact on human activities and the environment.

CRedit authorship contribution statement

Tianning Su: Writing – review & editing, Writing – original draft, Visualization, Validation, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Yunyan Zhang:** Writing – review & editing, Supervision, Project administration, Funding acquisition. **Youtong Zheng:** Writing – review & editing, Writing – original draft, Visualization. **Natalia Roldán-Henao:** Writing – review & editing, Writing – original draft. **Ralph Kahn:** Writing – review & editing, Supervision. **Zhanqing Li:** Writing – review & editing, Supervision, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare that they have no conflict of interest.

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Data availability

All data used in this study are obtained from published or open-access sources, which have been appropriately cited in the manuscript.

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