



Snow transitions to rain: A review of atmospheric melting layer studies using micro rain radar and complementary approaches

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ABSTRACT

The atmospheric melting layer (AML), where snow transitions into rain, influences satellite signals, precipitation remote sensing, and a range of hydro-meteorological applications. AML has been extensively studied using radar technology, but methods for continuous and consistent monitoring remain limited. This paper presents the first comprehensive review of AML research, with a focus on the Micro Rain Radar (MRR), a specialized precipitation profiler based on K-band frequency-modulated continuous-wave (FMCW) radar. We have organized the literature into four main themes: AML detection using MRR, comparisons with other instruments (e.g., radiosonde, scanning weather radar, satellite, and lidar) and reanalysis data, spatiotemporal variations in AML height, and methods for classifying precipitation event types (e.g., convective vs. stratiform). The in-depth critical review highlights strengths in the MRR's high temporal and spatial resolution, portability, and ability to continuously monitor precipitation microphysics. MRR provides multiple moments (e.g., reflectivity, and fall velocity) invaluable for AML studies, and their combination can enhance the consistency of AML detection, and event type classification. Nonetheless, limitations such as the single-polarization design, signal attenuation during heavy rainfall, and limited vertical range necessitate complementary datasets and advanced data processing techniques including artificial intelligence. Key findings underscore opportunities for gap filling and regionalization of AML observations, using mobile setups and multi-sensor campaigns. Also, modeling AML using surface weather variables can help link climate change studies and precipitation projections to anticipated AML behavior. The review concludes by outlining future directions and opportunities to advance AML research and applications.

1. Introduction

Most continental rainfall in mid-to-high latitudes originates from melting snow aloft (Fabry, 2015; Field and Heymsfield, 2015), known as “cold rain”. In contrast, “warm rain” originates solely from liquid phase precipitation and dominates over tropical oceans (Mülmenstädt et al., 2015). The dynamic altitude range where frozen/snow particles transition to rain is called the atmospheric melting layer (AML). AML formation is governed by microphysical and thermodynamic processes, including particle interaction and heat exchange. Thus, AML observations improve estimates of the weather profile (e.g., evaporation-related cooling rate, Xie et al., 2016b), as well as surface precipitation phase and

rate (Shates et al., 2023), important for weather simulation and forecast applications (Ikeda et al., 2005; Kumjian et al., 2016; Carlin and Ryzhkov, 2019; Brast and Markmann, 2020; Li and Moiseev, 2020; Zhu et al., 2022a; Konwar et al., 2012; Fehlmann et al., 2018). AML data support hydrological applications such as flood warning (Fehlmann et al., 2018), and influence satellite communication (Sarkar et al., 2014).

The AML upper and lower boundaries are defined as heights where completely frozen particles end, and completely liquid particles start, respectively. For non-turbulent, non-convective vertical profiles, the 0 °C isothermal height may estimate AML below it (Brast and Markmann, 2020; Kumjian et al., 2022). Due to the variability of the 0 °C isotherm (Benarroch et al., 2022), regular monitoring is essential. AML

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detection using in-situ measurements of temperature profile obtained by radiosonde may be inaccurate, e.g., when supercooled droplets do not freeze below 0 °C. Conversely, AML may appear at sub-freezing levels, e.g., during cyclones and convective updrafts (Qiao et al., 2022). Also, due to latent heat of fusion and cooling, snow may descend without melting above the 0 °C isotherm, which explains rather low correlations between freezing level and AML top level shown by Schauwecker et al. (2017). More sophisticated in-situ monitoring of AML is based on aircraft-mounted sensors (Di Girolamo et al., 2012; Giangrande et al., 2016; Kumjian et al., 2016).

However, in-situ observations are costly, impractical to perform constantly, and subject to the risk of icing of radiosonde (Vaugh and Schuur, 2018) and aircraft (Brast and Markmann, 2020; Kumjian et al., 2016). With suitable sensors onboard satellites, i.e., radiometers and radars (Konwar et al., 2012; Zhu et al., 2022a), AML observations are significantly extended, but suffer from limitations such as satellite radar blind zone (e.g., up to ~0.7–2 km heights depending on surface type) (Shates et al., 2023) as well as coarse resolution, or long revisit times.

Therefore, high-resolution AML studies typically use ground-based techniques like profiling radars or scanning weather radars (WR). Radar echoes respond to various characteristics of hydrometeors, e.g., particle size, number, and dielectric factor, requiring consistent interpretations for reliable identification of AML heights and processes. A well-known radar signature of AML is bright banding (BB) (Austin and Bemis, 1950): a band of enhanced reflectivity (Z) in the WR displays. Large, partially-melted snowflakes, before collapsing into raindrops, strongly scatter radar signals due to the liquid water's dielectric constant being ~5× that of ice (Evans, 1965). Below the AML, because of the divergence effect, i.e., fewer particles due to faster fall speeds of denser particles, Z drops (Di Girolamo et al., 2012; Kollias and Albrecht, 2005). Other AML-related radar signatures help to detect conditions such as dual BB (Das et al., 2010; Ikeda et al., 2005; Li and Moiseev, 2020; Martner et al., 2007) in elevated temperature inversion (Martner et al., 2007) or transition between events (Das et al., 2010), delayed or weakened BB due to riming (Giangrande et al., 2016), as well as saggy BB related to riming (Kumjian et al., 2016) or cooling with heavy precipitation falling into AML (Carlin and Ryzhkov, 2019).

AML studies use diverse radars such as zenith-pointing K-band Micro Rain Radar (MRR) (Brast and Markmann, 2020) and scanning S-band WR (Ikeda et al., 2005). High-frequency radars are more susceptible to path-integrated attenuation (PIA), and, thus, $PIA > 10$ dB for MRR could be removed from the AML analyses (Peters et al., 2005). Instead, low-frequency radars, e.g., C-band and S-band WRs, are less sensitive to smaller particles, partially responsible for their rainfall underestimation (Mazari et al., 2017). Further, the “cone of silence” above the maximum elevation angle of scanning WRs may not observe the desired range and resolution of AML for their coverage. For instance, the maximum elevation angle is typically 19.5° for the US's WSR-88D NEXRAD, 40° for the nationwide C-band WRs in Sweden, and 8° for the X-band WRs in south Sweden (Hosseini et al., 2022). Conversely, MRR is a portable, low-cost radar profiler specialized for high-resolution continuous measuring of drop size distribution (DSD) from consistent vertical ranges (Brast and Markmann, 2020).

Comparative studies of MRR-detected AML with observations from other instruments, such as radiosondes (Cha et al., 2009; Di Girolamo et al., 2012), lidars (Di Girolamo et al., 2012; Wei et al., 2022), and satellites (Das et al., 2011; Ramadhan et al., 2020), have been conducted across various locations (e.g., mountainous vs. coastal: Cha et al., 2009; Das et al., 2011) and seasons (e.g., pre-monsoon vs. monsoon, Longkumer et al., 2023, or summer vs. winter, Pfaff et al., 2014). These studies have enabled diverse applications, including bias correction of temperature lapse rates (Fehlmann et al., 2018), precipitation type classification (Sreekanth et al., 2019; Wang et al., 2021), and linking precipitation profile to surface weather (Hosseini et al., 2023b). MRR-detected AML has also been used for predicting ice albedo (Endries et al., 2018), glacial ablation estimates (Schauwecker et al., 2017), and

isotopic rainwater studies (Muller et al., 2015). These examples highlight the significant potential of MRR data and AML analyses, underscoring the need for a comprehensive review.

We explored the literature via three main searches in the TOPIC field of Web of Science Core Collection, a curated database with comprehensive indexes and searching features, namely:

- “AML” (a broad search about the melting layer)
- “AML + Radar” (limiting the “AML” search to the studies using radar technology)
- “AML + MRR” (limiting the “AML” search to the studies using MRR instrument)

These search labels are simplified representations. “Radar” covered radar or radars, “MRR” included both the abbreviation and full name of this instrument, and “AML” spanned variants like melting layer, freezing level, and bright band.

As shown in Fig. 1, the number of “AML” studies has increased much since the late 1980s. Comparing it to that of “AML + Radar” indicates the importance of radar in this development. The significant increase in studies during 2020–2024 is partly due to the inclusion of 2024 publications, unlike earlier bins in the histogram (the upper edge was not included for the other bins). However, as our last search was conducted on 2024-08-04, additional studies may yet appear due to database delays. The increase in the “AML + Radar” studies might be partially driven by the establishment of specialized instruments including MRR. Of the 74 studies of “AML + MRR”, 10 (13.5 %), 17 (23.0 %) and 35 (47.3 %) were from bins 2012–2016, 2016–2020, and 2020–2024, respectively. Representing these numbers as fractions of the corresponding “AML + Radar” counts, i.e., 6 % ($=10 \div 166$), 9 % ($=17 \div 193$), and 12 % ($=35 \div 297$) indicate a significant increase in the relative contribution of MRR in the radar-based AML studies.

Despite two decades of AML research using MRR, the “AML + MRR” search revealed no review papers. Even the review papers from our broader “AML” search, summarized in Table 1, were neither comprehensive nor specifically focused on AML observations. Thus, based on our search, this paper represents both the first specialized review of “AML + MRR” studies and the most comprehensive review of “AML” to date, incorporating perspectives from diverse instruments frequently studied alongside MRR. Notably, most of the studies reviewed here involved multiple instruments and signatures of AML, highlighting MRR's growing role in AML research since 2004 (Fig. 1). We synthesized insights from these studies into structured discussions, focusing on comparative aspects, and concluded with recommendations for future integrative suites and data-consolidation methods for more consistent interpretations. This approach aligns most closely with prior work by Dias Neto et al. (2019) that analyzed two months of winter precipitation using dual-wavelength ratios (DWRs) from collocated zenith-pointing X-, Ka- and W-band radars.

2. Technical overview of MRR

This section introduces the technical specifications of MRR, useful for the next sections, where it is compared with other AML observation approaches in the literature.

MRR, manufactured by METEK GmbH, is a frequency-modulated (FM) continuous-wave (CW) K-band (~24 GHz) radar, allowing operations typically used in a vertically pointing configuration (Brast and Markmann, 2020). Fig. 2 shows an MRR in Lund, Sweden. With a 1.5° beam divergence (Wei et al., 2022), the sampling area expands with height (e.g., ~193 m² at 450 m) (Konwar et al., 2012). The off-axis antenna drains water without building ponds. A heating unit can be attached to the backside of the antenna to avoid icing or snow accumulation. Having a fixed-oriented small antenna (vs. rotating/tilting antenna of large WRs), MRR is a low-power and portable instrument, designed for high-resolution profiling of precipitation microphysics,

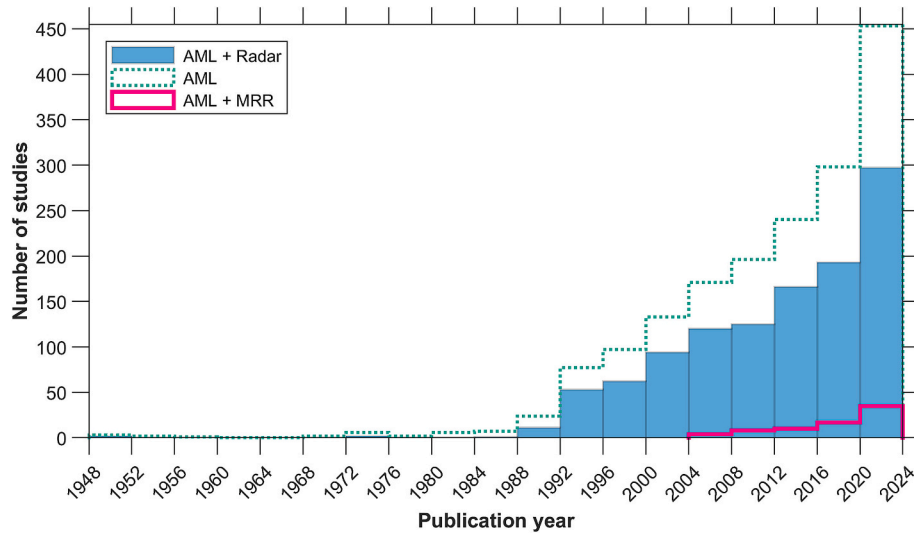


Fig. 1. The number of studies found by the Web of Science searches, namely: “AML”, “AML + Radar”, and “AML + MRR”, annotations representing the broader search phrases behind them.

Table 1

Summary of review papers found by the “AML” search.

Focus of the review	AML-related highlights
Errors in quantitative precipitation estimation (QPE) by pulsed radar (Villarini and Krajewski, 2010)	Different corrections for variable aloft (vs. ground) reflectivity of different storms
Latent heat estimation for TRMM PR: Tropical Rainfall Measuring Mission's Precipitation Radar (Shige et al., 2009)	Highly sensitive results to estimated fraction of stratiform rain at AML level
Low-latitude convection variation for TRMM PR (Houze Jr. et al., 2015)	Detection of wide convective cores as stratiform
Auto-conversion for orographic precipitation (Xiao et al., 2021)	Cloud-aerosol interaction model considering melting microphysics
Mass and heat budget for aerosol-induced precipitation change (Khain, 2009)	Clouds with high freezing levels
Dual-polarization radar observing precipitation microphysics (Kumjian et al., 2022)	Variable polarization contrasts for diverse shapes of melting particles
Decline of snow and ice in the tropical Andes (Vuille et al., 2018, Vuille et al., 2008)	Rising temperature and freezing level
Operational radar hydrology in Canada (Wijayarathne and Coulibaly, 2021)	Low-level BB errors for high latitude QPE, MRR a recommended solution
Analyzing 2-month winter precipitation observations for a German site by triple-frequency zenith-pointing radars (Dias Neto et al., 2019)	Maximized DWRs close to AML
Opportunistic rainfall rate estimation from attenuation in satellite links to local receivers (Giannetti and Reggiani, 2021)	Needs to distinguish contributions from liquid and melting layers

providing a specialized, cost-effective alternative to larger WRs with limitations mentioned in the Introduction section.

The core functionality of different MRR variants (e.g., MRR-2 or MRR-PRO) involves measuring Doppler spectra (from varying fall velocity of drops) to directly estimate DSD, and related parameters such as reflectivity Z (dB), liquid water content LWC (g m^{-3}), and rainfall rate R (mm/h), based on the Rayleigh approximation:

$$Z = \int_{\min D}^{\max D} N(D)D^6 dD \quad (1)$$

$$\text{LWC} = \rho_w \frac{\pi}{6} \int_{\min D}^{\max D} N(D)D^3 dD \quad (\rho_w : \text{water density}) \quad (2)$$

$$R = \frac{\pi}{6} \int_{\min D}^{\max D} N(D)D^3 v(D) dD \quad (3)$$

where D , $N(D)$, and $v(D)$ denote drop diameter, number, and fall velocity, respectively. Therefore, the MRR algorithms are different from the indirect methods normally used for estimating DSD by scanning

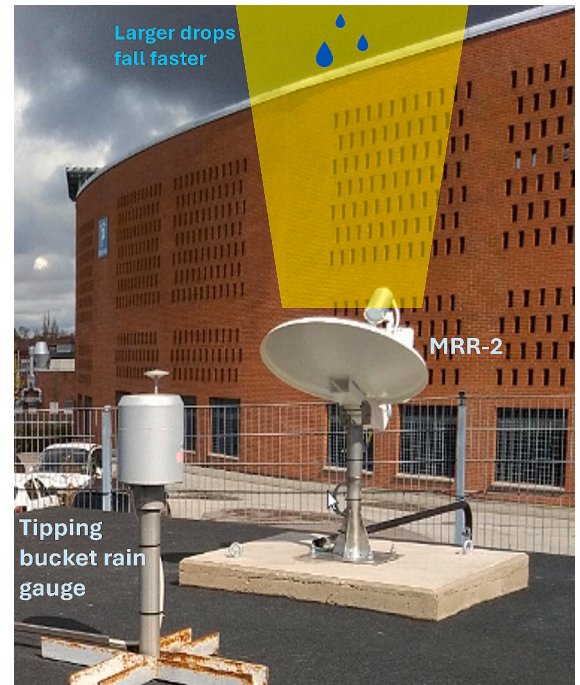


Fig. 2. Comparable sizes of an MRR and a rain gauge collocated in a weather station operated by the water utility company VA Syd in Lund, Sweden. The MRR beam path is schematized in transparent yellow. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

weather radars (Lee et al., 2023). Unlike conventional methods (Marshall and Palmer, 1948; Ulbrich and Atlas, 1998) that assume drop distributions, MRR derives DSD directly from Doppler spectra based on the FMCW principles (Barrick, 1973; Strauch, 1976).

In contrast to pulsed radars, which determine target range by measuring time delays between discrete pulses, MRR derives it based on the frequency shifts between continuously transmitted and received signals (see the schematic in Fig. 3). There is a tradeoff between MRR's range resolution and maximum range, with typical choices of 30–200 m and 1–6 km, respectively. Path-integrated attenuation (PIA) at longer ranges is non-negligible and must be accounted for (Peters et al., 2010). While MRR-2 uses a fixed number of range gates (32), MRR-PRO allows adjustments between 32 and 256 gates, enabling higher flexibility in data resolution and data acquisition time. However, falling hydrometeors cause both range-related frequency shift and Doppler shift in received signals. This introduces a range-velocity ambiguity, which is resolved based on phase measurements (Barrick, 1973). In addition, maximum detectable (Nyquist) velocity by MRR-2 is 12.08 m/s, above which phase measurements can wrap around, and result in underestimation of fall velocity. Therefore, some studies recommend de-aliasing routines for MRR data (Garcia-Benadi et al., 2020; Maahn and Kollias, 2012).

FMCW processing separates drops of varying fall velocity using power spectra to estimate the number of superposed contributors (i.e., equal-sized drops, falling at undetectable speed differences, e.g., <0.13 m/s for MRR-2). The process relies on the terminal velocity of raindrops (Atlas et al., 1973) and a height-dependent raindrop density correction (Peters et al., 2020). To reduce sampling error, the data acquisition records averaged spectra every 10 s, and the MRR software calculates noise-eliminated and attenuation-corrected “Averaged Data” every minute.

Thus, MRR estimates R and LWC directly, without relying on the empirical relationships (Mazari et al., 2017). Similarly, the characteristic fall velocity (W) is estimated as the first moment of Doppler spectra at a range around the spectral peak, or the center of gravity of the spectra (Peters et al., 2020). Other variables obtained using spectral data (e.g., equivalent reflectivity, Z_e) are described elsewhere (Peters et al., 2005; Peters et al., 2002; Wang et al., 2017). Finally, MRR-PRO has a new built-in AML product that uses deep learning to generate probability profiles (values from 0 to 1, with >0.75 indicating AML) (Brast and Markmann, 2020; Garcia-Benadi et al., 2021).

3. Review of melting layer studies using MRR

As introduced earlier, the “AML + MRR” search yielded 74 studies.

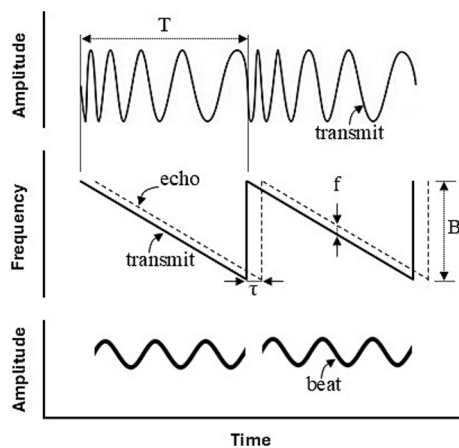


Fig. 3. FMCW observation of a resting point target during two complete sweeps. Top: FM transmit signal. Middle: transmit and echo frequencies. Bottom: beat signal with no sampling during first τ period of the consequent sweep.

As shown in Fig. 4, most studies were conducted in western Europe (primarily Germany and Spain), India, and China, followed by the Americas (mainly the US, Peru, and Bolivia). In contrast, there are few studies from Eastern Europe, Central and Western Asia, Africa, Central America, and the northernmost and southernmost regions globally. Nevertheless, the compiled literature encompasses a variety of climate zones.

Following a full-text review of the relevant studies (as summarized in Table S1), their relevant details are organized and presented in four main sub-sections: (3.1) AML detection methods using MRR, (3.2) alternative instruments and reanalysis data compared with MRR-detected AML, (3.3) spatiotemporal variations of AML height and thickness, and (3.4) classifying event types. In addition, where appropriate, the review is supported by additional studies cited within the ones primarily reviewed. In-depth discussions, and conclusions are provided in separate sections (Sections 4 and 5).

3.1. Methods for AML identification

MRR profiles of reflectivity or fall velocity are commonly used to detect AML. The simplest approach involves visual inspection of these profiles for peaks within or around AML (Fig. 5). Full Doppler spectra can also indicate increased spectral width within the AML (Khanal et al., 2019). 2D histograms of reflectivity or velocity over time and height (e.g., Shates et al., 2023) (Fig. 6a), sometimes in the form of Contoured Frequency by Altitude Diagrams (CFADs) (Cao et al., 2023; Goenka et al., 2023; Raut et al., 2021; Zhou et al., 2024) (Fig. 6b), are also widely used. More sophisticated methods are discussed in the following.

3.1.1. Modeling vertical profile of reflectivity (VPR)

AML detection often relies on identifying a reflectivity peak just below the freezing level, where snowflakes are partially melted (Di Girolamo et al., 2012; Di Girolamo et al., 2009; Wang et al., 2021). Long-term AML analyses require automated modeling of the vertical profile of reflectivity (VPR), typically using a theoretical profile such as a piecewise linear model (Kitchen et al., 1994; Pfaff et al., 2014). The VPR model characterizes the AML using a few parameters, including height of peak reflectivity, difference between peak reflectivity and a constant base reflectivity, and AML thickness, i.e., difference between AML top and bottom heights.

The VPR model assumes that the AML peak is located midway between the bottom and top levels. Then, it solves an optimization problem that, provided a proper convergence, can estimate the model parameters. Since the optimization process is initialized using the parameters from the previous time step, convergence becomes most difficult when measurements are unstable over time, e.g., during onset of precipitation events (Pfaff et al., 2014). Moreover, the condition of constant reflectivity below the AML is not always met. For example, following a local peak, reflectivity can increase towards the surface when the collision-coalescence process dominates over collision-breakup (Raut et al., 2021).

3.1.2. Vertical gradient of reflectivity (VGR)

Lower in the AML, as snow transitions into rain, reflectivity decreases due to the smaller size and lower number density of faster-falling raindrops compared to snowflakes (Di Girolamo et al., 2012; Di Girolamo et al., 2009). Vertical gradient of reflectivity (VGR) is a method to estimate the AML bottom and top levels by identifying the largest positive and negative upward gradients, respectively. The height of maximum reflectivity indicates the peak level (Rajasekharan Nair, 2020). As proposed by Cha et al. (2009), and applied elsewhere (Cao et al., 2023; Jash et al., 2019), the method requires the peak level to lie between the estimated bottom and top. Otherwise, no AML is detected (Sumesh et al., 2019). Pfaff et al. (2014) modified the method to ensure a sufficiently distinct BB.

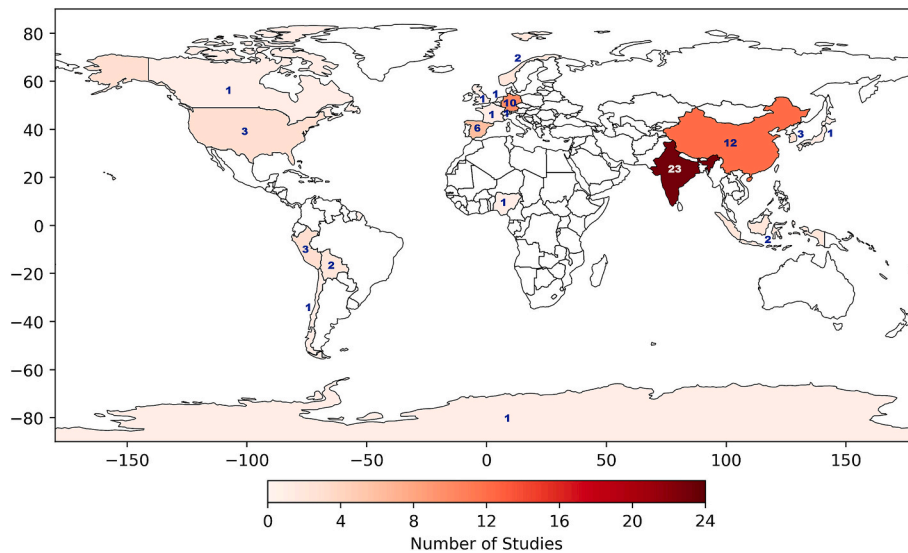


Fig. 4. Number of the “AML + MRR” studies per country.

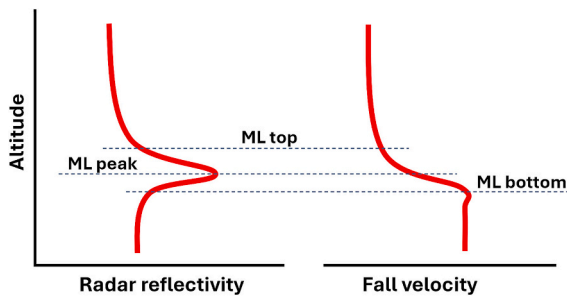


Fig. 5. Schematic of the instantaneous/mean MRR profiles of reflectivity (left) and velocity (right), typical for a stratified AML.

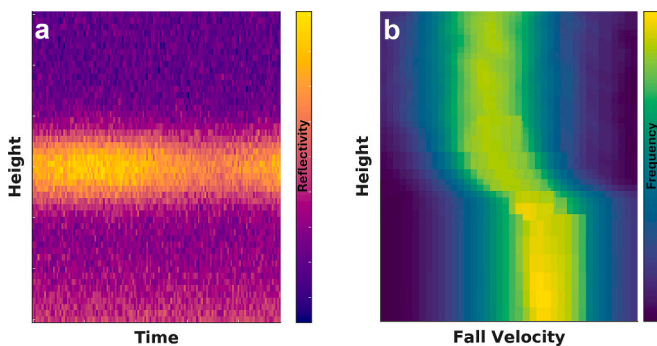


Fig. 6. Schematic of the 2D histograms of reflectivity time series (a), and CFAD of fall velocity (b).

3.1.3. Velocity auxiliary methods

The profile of MRR's characteristic velocity typically consists of three zones:

- a relatively constant, low velocity above the AML,
- a rapid increase of velocity within the AML, and
- a high, nearly constant velocity below the AML.

Since the maximum velocity occurs at a lower height than the peak reflectivity, the vertical gradient of fall velocity (GFV) and VGR can be combined, such that the most negative GFV and most positive VGR estimate AML bottom and top, respectively (Wang et al., 2017). However,

quality control is necessary to filter unrealistic profiles such as those exhibiting an abnormally thick BB (Schauwecker et al., 2017). The GFV-based AML boundaries were visually validated by overlaying them with corresponding profiles of MRR variables such as reflectivity and LWC for stratiform events in Kototabang, Indonesia (Ramadhan et al., 2020). Inspecting normalized velocity profiles (scaled between 0 and 1) for certain thresholds (e.g., 0.8) is also used to bound the search for peak reflectivity level. Applied to summer and winter events in southwest Germany, this method outperformed both the VPR and VGR approaches (Pfaff et al., 2014).

Additional methods based on advanced Doppler spectral processing, i.e., RaProM and RaProM-Pro for MRR-2 (Garcia-Benadí et al., 2020) and MRR-PRO (Garcia-Benadí et al., 2021), provide improved treatment of noise, and Doppler de-aliasing. These schemes are suggested to create a more complete and realistic AML time series than those produced by default MRR processing. To further reduce noise in time series analyses, hourly median values (Schauwecker et al., 2017) or moving-averaged profiles (Benarroch et al., 2022) have also been applied.

3.1.4. Other profiles

More distinct BB signatures are often observed in the rain rate (R) profiles than in reflectivity (Z) profiles from MRR (Das et al., 2011; Mehta et al., 2020; Xie et al., 2016b).

In contrast, LWC profiles may show AML-like signatures during periods without rainfall (Mazari et al., 2017). This can be attributed to LWC's weaker dependence on drop diameter (D^3 vs. D^6) and its independence from fall velocity (v), in contrary to R (see Eqs. (2)–(3)). The MRR-derived spectral width was shown less useful for AML delineation, e.g., compared to that of a Doppler lidar (Wei et al., 2022).

Some studies have examined Dual Wavelength Ratios (DWRs) as ratios of reflectivity from MRR to that from other frequency radars. DWR values tend to remain near zero under Rayleigh scattering (smaller drops), while increasing under non-Rayleigh scattering (Chellini et al., 2022).

3.1.5. Artificial intelligence (AI) models

MRR provides continuous, high-resolution observations of the lower atmosphere (up to several kilometers), making it well-suited for training data-driven models using artificial intelligence (AI).

However, we found only one study employing this approach: Brast and Markmann (2020) developed a neural network (NN) with two hidden layers (64 neurons each) based on several months of MRR-PRO observations, primarily from Hamburg and Hohenpeißenberg, and

partially from Elmshorn, Germany. For training, AML top and bottom heights were manually labeled by visually inspecting 2D histograms of multiple MRR variables. These labels were then translated into a probabilistic output (0–1) based on the standard deviation of AML height estimates across variables.

Input features were time-lagged sequences of attenuated equivalent reflectivity and Doppler velocity at 0, 6, 12, 18, and 24 time steps (10-s intervals). This sequential input offers an advantage over methods like VGR and GFV, which treat profiles independently. However, the NN, like VPR model, may still produce unreliable results in rapidly evolving AML conditions.

While the model's performance was monitored using mean squared error (MSE) on a validation set during training, no additional profiles were labeled for post-training verification. Instead, NN outputs were visually inspected against new MRR profiles, and compared with additional observations from nearby weather radars, radiosondes, and a cloud radar. These comparisons showed general agreement, although spatial and resolution mismatches sometimes limited precision.

Sensitivity analyses also showed that the NN performed well across MRR configurations with different vertical (25–100 m) and temporal (10 s to 1 min) resolutions, with only minor degradation under more coarsely averaged input data (Brast and Markmann, 2020).

While our review focused on MRR methods, other studies (e.g., Xie et al., 2025) have used machine learning for AML detection with different radars and can therefore be reviewed elsewhere.

3.2. Complementary instruments and reanalysis products

MRR-based AML estimations, like other remote sensing methods, are susceptible to errors. In the absence of reliable reference data, cross-comparison with other instruments is commonly used for evaluating accuracy of the estimations.

3.2.1. Ground-based radars

We categorized studies comparing MRR-detected AML with other ground-based radar data based on the instrument type, and observed variables, namely:

- Scanning WRs – reflectivity or rainfall intensity

- Radar profilers – reflectivity or velocity
- Dual polarization radars – depolarization or cross-correlation

When relevant, additional distinctions such as radar frequency bands are discussed. Notably, Rayleigh scattering assumes raindrop diameters are no larger than one-tenth of the radar wavelength; otherwise, the sixth-power dependence on D (Eq. (1)) becomes invalid for part of the DSD (i.e., non-Rayleigh conditions). For consistency, we followed the IEEE standard for radar band naming (see Table S2), which explains why the original designations, e.g., 35 Hz as K-band (Sassen et al., 2005) and 1.29 GHz as UHF (Di Girolamo et al., 2012; Di Girolamo et al., 2009) are referred to here as Ka and L bands, respectively.

3.2.1.1. Scanning WRs – Reflectivity and rainfall intensity. WRs' BB signatures for stratiform precipitation provide a useful reference for AML analysis (Mazari et al., 2017; Pfaff et al., 2014; Wei et al., 2022). Modern WRs also provide polarimetric variables that aid in attenuation correction (Hosseini et al., 2023a; Hosseini et al., 2020) and microphysical interpretations relevant to AML (Raut et al., 2021).

MRR-detected AML heights can be projected onto WR reflectivity or rainfall rate maps as circles, indicating the range at which the WR beam intersects AML height. We applied this method using the MRR in Lund and its nearby X-band WR. The results allow inspection of spatial consistency between AML signatures from both systems (see Fig. 7).

Brast and Markmann (2020) analyzed 90 and 84 MRR-detected AML cases in Hamburg and Hohenpeißenberg, Germany. Of these, only 35 and 18 cases, respectively, were confirmed by at least one of the three C-band WRs covering the MRR sites. The limited agreement was attributed to long horizontal distances between the MRRs and the WRs (40–90 km), which reduced vertical resolution of WRs compared to MRR (700–1500 vs. 25 m). This mismatch hindered accurate co-detection of AML heights. In Tuljapur, India, CFAD plots based on an MRR and a co-located C-band WR reflectivity revealed similar AML characteristics, particularly during widespread stratiform rainfall (Raut et al., 2021). Notably, stratiform clouds with embedded convection may still lack visible BB signatures in horizontal radar projections (Zhu et al., 2022b).

3.2.1.2. Radar profilers – Reflectivity or velocity. Vertically-pointing radar profilers operate across a wider range of frequencies than typical

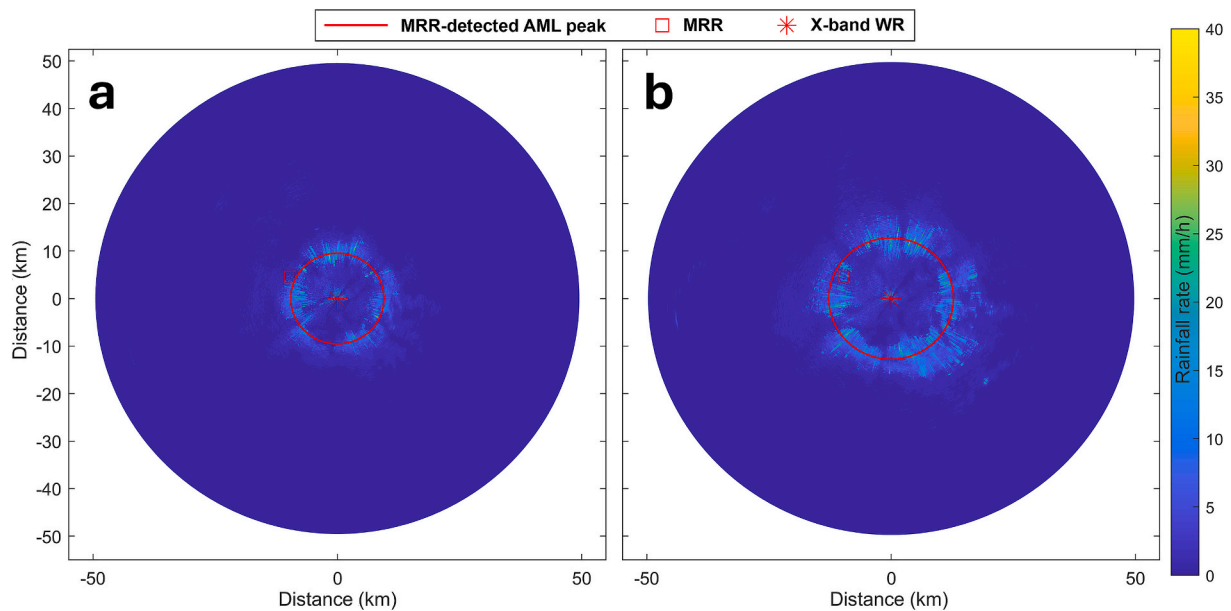


Fig. 7. AML peak height detected by the MRR-2 in Lund at 2021-10-15 06:00, superimposed as red circles on rainfall intensity maps from a nearby X-band WR. The circles illustrate how the projection radius increases with decreasing WR elevation angle: 8° (a) and 6° (b). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

X- to S-band scanning WRs. For instance, a 35.5 GHz (Ka-band) cloud radar and a 1.29 GHz (L-band) wind profiler provided similar AML peak estimates to those from the MRR during a stratiform summer rainfall event in Achem, Germany (Di Girolamo et al., 2012; Di Girolamo et al., 2009). However, the MRR estimated higher velocities, likely due to the greater sensitivity of its K-band frequency to larger, faster-falling particles, as the Doppler velocity has known tendency to emphasize specific parts of the DSD, depending on frequency (Sassen et al., 2005). Frequency also influences reflectivity, as different drop sizes contribute variably across bands. Consequently, the BB signature appeared sharper in MRR data than in either the cloud radar or wind profiler (Di Girolamo et al., 2012; Di Girolamo et al., 2009). Similar comparison during Typhoon Yagi in Shandong, China, also showed agreement between MRR and Ka-band cloud radar reflectivity profiles (Wang et al., 2021).

Ka-band BB signatures are typically weaker than those at S-band, due to mixed Rayleigh and non-Rayleigh scattering (Sassen et al., 2005). At 94 GHz (W-band), sub-millimeter drops dominate reflectivity, as non-Rayleigh scattering minimizes contributions from larger drops (Kollias and Albrecht, 2005). This can lead to a reflectivity plateau below the 0 °C isotherm, as seen during a weak stratiform event in Florida (Kollias and Albrecht, 2005). W-band profilers may show no BB due to dominant non-Rayleigh scattering, which could be insensitive to large water-coated snowflakes higher in the AML (Sassen et al., 2005). Similar processes likely caused BB disruption observed by a Ka-band profiler during heavy summer rainfall in Miami (Sassen et al., 2005).

Gaps in AML observations may also be inevitable during heavy rainfall that attenuates high-frequency signals. Thus, periods with stable BB heights are recommended for reliable AML analysis (Perry et al., 2017; Rawat et al., 2022; Rojas et al., 2021; Sumesh et al., 2019). Continuous MRR data help reduce misidentifications through smoothing out temporary AML anomalies over time (Das et al., 2010).

3.2.1.3. Dual polarization radars – Depolarization or cross-correlation. The diverse shapes of melting particles induce polarization contrasts, typically more pronounced for snow than for hail (Kumjian et al., 2022). At Ka-band, the linear depolarization ratio (LDR) was found to mark the AML bottom detected by MRR (Brast and Markmann, 2020). However, AML signatures can vary across radar bands. LDR showed higher sensitivity than reflectivity at Ka-band, whereas attenuation was less problematic at MRR's frequency (Kowalewski and Peters, 2010). The agreement between AML heights from MRR's reflectivity and a Ka-band LDR-based method suggests their potential use as mutual references (He et al., 2021).

In a study combining MRR and dual-polarization X-band WR, the asymmetric profile of cross-polar correlation (RHOHV) emerged as the most reliable AML indicator, and the peak Doppler velocity from MRR aligned with the AML bottom detected via RHOHV (Khanal et al., 2019). Similar findings have been reported in other studies (Xie et al., 2016a).

3.2.2. Radiosonde

Radiosondes were widely used across the reviewed studies. At two distinct Korean sites, MRR-derived AML tops correlated well with the 0 °C isotherm, with a correlation of 0.72 and RMSE of 330–370 m (Cha et al., 2009). Similar consistency was reported for a case in Jinan, China (Wang et al., 2017) and monthly mean AML heights across northern and southern India (Das et al., 2011). In a German summer event, the BB peak lay ~400 m below the 0 °C level, around the 4 °C isotherm (Di Girolamo et al., 2012; Di Girolamo et al., 2009). The 0 °C dry- and wet-bulb isotherms are occasionally used to approximate BB top and bottom (Garcia-Benadi et al., 2021).

Radiosonde-derived relative humidity is useful for calculating wet-bulb temperature (Wang et al., 2021), while Convective Available Potential Energy (CAPE) help analyze correlations with AML characteristics (Saha et al., 2023). Sub-saturated AMLs tend to be thicker than saturated ones (Poirier et al., 2019). In addition, precipitation can

reshape local temperature profiles (Stewart et al., 1984). For instance, sublimation cooling may delay melting onset by ~100 m per 10 % sub-saturation (Mitra et al., 1990).

Radiosondes typically operate at long intervals—e.g., twice daily (Benarroch et al., 2022; Fehlmann et al., 2018) or twice weekly (Brast and Markmann, 2020)—limiting direct temporal comparison with MRR data. Garcia-Benadi et al. (2021) assessed MRR–radiosonde AML height differences within ± 1.5 h of launch times. Spatially, comparisons remain valid during widespread stratiform events, even when MRR and radiosonde sites are far apart (Di Girolamo et al., 2012). Accordingly, several studies classify event types (Das et al., 2009; Rajasekharan Nair, 2020) and exclude non-stratiform cases from AML evaluations (Cha et al., 2009). Radiosonde data also helped exclude AML estimates during inversion periods (Fehlmann et al., 2018).

3.2.3. Radiometer

Unlike in-situ radiosonde observations, radiometers are passive ground-based remote sensing tools that retrieve temperature profiles by measuring atmospheric thermal radiation, expressed as brightness temperature (Halder and Maitra, 2020). Increases in velocity and reflectivity below the radiometer-derived 0 °C level (Garcia-Benadi et al., 2020) support their use as proxies for radiosonde data. Radiometers provide continuous, non-intrusive observations from broader ranges; however, they require more intensive calibration and offer coarser vertical resolution compared to radiosondes.

3.2.4. Surface sensors

Near-surface in-situ sensors provide only indirect support for AML studies. Some hydrologic models, such as the European Flood Alert System, rely on empirical or modeled lapse rates derived from interpolated surface temperature (Fehlmann et al., 2018; Schauwecker et al., 2017). In a Swiss catchment, lapse rates of 0.55 °C/100 m (wet-bulb) and 0.58 °C/100 m (dry-bulb) systematically overestimated the snowfall level (ML top), which was later bias-corrected using MRR profiles (Fehlmann et al., 2018).

Disdrometers help assess how microphysical processes—with or without a BB aloft—influence surface DSD (Jash et al., 2019; Konwar et al., 2012; Rajasekharan Nair, 2020). Optical disdrometers (Garcia-Benadi et al., 2021; Wei et al., 2022) use laser beams between two parallel surfaces to detect passing drops. Video disdrometers rely on high-speed imaging (Shates et al., 2023), while impact disdrometers (Das et al., 2010; Rajasekharan Nair, 2020; Sarkar et al., 2014) measure drop momentum upon contact. Updrafts or downdrafts primarily affect impact disdrometers, while overlapping drops introduce errors in all types.

Disdrometers may infer AML presence (though not its height) from differences in Z–R relationships between convective and stratiform rain (Mehta et al., 2020; Rajasekharan Nair, 2020). MRR and disdrometer estimates of rainfall rate (R), reflectivity (Z), and median drop diameter were consistent during low to moderate summer rainfall in Jinan, China (Wang et al., 2017). Similar results were reported from an Indian coastal site (Rajasekharan Nair, 2020). However, in one inversion event, an optical disdrometer misclassified sleet as rain (Peters et al., 2020). Also, discrepancies in DSD shapes—particularly for drop sizes <1 mm or >3 mm—have been reported (Jash et al., 2019; Sarkar et al., 2015). The differences may stem from spatial mismatches between MRR and disdrometer locations (Di Girolamo et al., 2012) or from instrument-specific limitations such as MRR signal attenuation or disdrometer laser inhomogeneity (Jash et al., 2019).

3.2.5. Aircraft mounted sensors

Aircraft-mounted sensors such as 2D optical probes, typically accompanied by altitude and temperature sensors, provide a less common means of in-situ AML observation (Di Girolamo et al., 2012). The probe functions similarly to an optical disdrometer, using photodiodes to detect shadows cast by passing hydrometeors. High-rate sampling

produces 2D time-series images, where black spots of varying size and shape represent the hydrometeors.

An aircraft ascent through an AML in Achern, Germany, captured features such as rimed snowflake aggregates near the freezing level and their collapse below. These observations were validated using co-located radiosonde and MRR data (Di Girolamo et al., 2012). Below the AML, MRR and probe measurements of the drop size spectra showed good agreement. Mean drop diameter estimates from both also aligned with those from a ground-based disdrometer 27 km away. However, the disdrometer recorded fewer small drops (Di Girolamo et al., 2012). These underestimations likely resulted from evaporation during fall (Xie et al., 2016b), limited detection of small drops ($D < \sim 0.25$ mm), and smaller sampling volume of disdrometers (Garcia-Benadi et al., 2020).

A key limitation of aircraft-mounted probes is their reliance on fixed flight paths and times, resulting in sparse and discontinuous sampling (Wang et al., 2017).

3.2.6. Lidar

Ground-based lidars offer remote sensing alternatives for AML monitoring. For example, the 1064-nm CHM 15 k Nimbus ceilometer can profile backscatter up to 16.8 km with 15 m resolution (Sumesh et al., 2019). Lidar backscattering follows geometric optics—scaling with the square of particle diameter and significantly influenced by particle shape and phase—unlike the sixth-power dependency in Rayleigh radar scattering (Sassen et al., 2005).

Upward-pointing lidars may exhibit a “dark band” (a region of minimal backscatter) near the AML peak, where radar Doppler velocity is maximized (Di Girolamo et al., 2012; Di Girolamo et al., 2009; Sassen et al., 2005), due to reduced particle size and concentration. Below the AML, lidar echoes may increase again due to dominant backscattering from spherical particles (Sassen and Chen, 1995). During a light summer rainfall in Achern, Germany, lidar backscatter showed a weak peak 100–200 m below the dark band, and a stronger peak near the 0 °C isotherm (Di Girolamo et al., 2012). For lidar wavelengths of 355–1064 nm and radar frequencies of 1.29–35.5 GHz (including MRR), the lidar dark band appeared slightly below the radar BB (Di Girolamo et al., 2012). Notably, the lidar telescope lacked precipitation protection, so useful data were limited to pre-rainfall periods (Di Girolamo et al., 2012; Di Girolamo et al., 2009).

Beyond vertically-pointing systems, azimuth-scanning lidars also support AML detection. A 1.55- μ m coherent Doppler lidar scanning at a 65° elevation angle with 2-min intervals was used in eastern China (Wei et al., 2022). This eye-safe wavelength is less affected by atmospheric turbulence and solar radiation, enabling all-day operation. The AML heights detected under 0–1.7 mm/h rainfall matched BB signatures observed by a collocated MRR and an S-band WR (Wei et al., 2022). However, the typical dark band seen with shorter wavelengths (Di Girolamo et al., 2012; Di Girolamo et al., 2009; Sassen et al., 2005) was less prominent at 1.55 μ m. Still, the lidar’s profile of spectrum width revealed a clear BB, demonstrating its complementary role alongside MRR (Wei et al., 2022).

3.2.7. Satellite

AML-related signal attenuation affects satellite links—especially above 10 GHz—at levels comparable to long path-integrated attenuation due to rain (Das et al., 2011; Xian et al., 2021). The impact intensifies along oblique satellite paths due to extended propagation through melting particles, as confirmed by MRR data (Xian et al., 2021).

The 13.8 GHz (Ku-band) Precipitation Radar aboard TRMM (1997–2015) retrieved precipitation profiles up to 20 km altitude across the tropics (35°S–35°N), with 250 m vertical and 4.3 km horizontal resolution, and a detection sensitivity of 0.7 mm/h (Das et al., 2011). Various TRMM products supported AML studies. TRMM 2A23 and TRMM 3A25 showed good agreement with MRR-derived BB heights in Nigeria (Ojo et al., 2014), and India (Das et al., 2011). Similar consistency was found in Indonesia using TRMM 2A25 profiles at low

incidence angles ($< 7^\circ$) (Ramadhan et al., 2020). Finding paths with an associated low angle of incidence is challenging in some regions, as reported for Kolkata, India (Rakshit and Maitra, 2016). Over high terrains (e.g., Andes, and Himalayas), TRMM failed to detect BB due to ground echo interference—a limitation mitigated by deploying MRR in nearby valleys (Schauwecker et al., 2017; Schauwecker et al., 2016).

The GPM core observatory, a successor to TRMM, carries a dual-frequency (Ka- and Ku-band) precipitation radar (DPR) and a multi-channel microwave radiometer (10–183 GHz), enabling enhanced precipitation and BB retrievals via improved sensitivity (~ 0.2 mm/h) and extended coverage (65°S–65°N). However, clutter removal algorithms can misidentify low-altitude AMLs (Watters et al., 2018), a gap MRR can help address (Shates et al., 2023). In Indonesia, MRR-derived DSD diverged from DPR estimates, especially during convective rain, possibly due to inadequate attenuation correction of MRR (Marzuki et al., 2023). Over the Southern Ocean, shipborne MRR data showed consistency with GPM radiometers, despite the limited number of collocations studied (Goenka et al., 2023).

CloudSat (2006–2023) carried a 94 GHz (W-band) radar to observe cloud and precipitation vertical structure at ~ 500 m vertical and 1.7 km horizontal resolution (Ferraro et al., 2018; Stephens et al., 2002). In Pune, India, CloudSat BB signatures matched MRR reflectivity peaks during light stratiform rain (Konwar et al., 2012). In contrast, a ground-based 94 GHz profiler in Florida missed a BB detected by a 3 GHz profiler (Kollias and Albrecht, 2005). Differences between the down-looking and up-looking 94 GHz radars in Pune and Florida may reflect variations in DSD under non-Rayleigh conditions. Alternatiely, the BB signature observed by CloudSat could result from rapid attenuation of downward traveling W-band signals encountering melting particles with a high refractive index.

Following CloudSat’s termination, EarthCARE, launched in May 2024, now carries a 94 GHz radar with Doppler capability—offering new opportunities for AML studies and MRR comparisons (Wehr et al., 2023).

3.2.8. Reanalysis

Reanalysis datasets provide globally consistent temperature and humidity profiles that could be indirectly useful for AML studies. Hourly ERA5 and 3-hourly MERRA-2 datasets with corresponding grid sizes of 0.25° and 0.5° offer vertical profiles across 37 and 42 pressure levels, respectively. Converting pressure levels to height above ground requires applying hydrostatic and hypsometric formulas, and coarse grid resolutions limit local accuracy of AML approximations (Benarroch et al., 2022). However, wet-bulb 0.5 °C and 1 °C isotherms from these two datasets correlated well with GFV peaks derived via MRR (Shates et al., 2023).

At Kohima, India, seasonal ERA5-based 0 °C isotherms confirmed the MRR-observed AML height difference between pre-monsoon (2.5 km) and monsoon (3.5 km) (Longkumer et al., 2023). In Madrid, Spain, longterm and monthly average 0 °C heights showed good agreement with ERA5 estimates (Benarroch et al., 2022). MRR-derived AML top levels also generally matched ERA5 0 °C levels during several events, though deviations occurred during intense rain (Benarroch et al., 2022).

ERA5’s CAPE product also showed some correlation with MRR-detected AML heights (Saha et al., 2022), while its cloud LWC product exhibited stronger correspondence to AML thickness derived from MRR (Saha et al., 2023).

3.3. Variation of AML properties and processes

The AML height and thickness vary geographically (e.g., mountain vs. coastal), and temporally (e.g., winter vs. summer, or monsoon vs. pre-monsoon). Understanding the underlying microphysical processes governing these variations is key to develop AML-related knowledge and applications.

3.3.1. Geographical variation

At a northern Himalayan site, MRR detected significant seasonal changes in AML height, in contrast to a southern coastal site in India where surface temperature, and consequently AML heights, remained relatively stable year-round (Das et al., 2011). In Chile, MRR was operated with finer range resolution at a mountainous site than at a coastal one, due to the lower AML height (Rojas et al., 2021).

In South Korea, daily mean MRR profiles showed a thicker AML at a mountain site, along with a weaker reflectivity gradient, lower peak reflectivity, and smaller variability compared to a coastal site (Cha et al., 2009). These differences are shaped by underlying microphysical processes. For example, larger snow particles melt more slowly, and create a thicker AML (Kim and Lee, 2016). Snow density also plays a critical role: denser particles fall faster and melt more slowly, also resulting in thicker AML with a weaker reflectivity gradient. Snow density varies geographically (Zawadzki et al., 2005), which explains the contrast observed in Korea, where the coastal site exhibited a wider range of snow types, while the mountain site predominantly exhibited dense, rimed snowflakes (Cha et al., 2009).

By contrast, averaged MRR profiles showed a more prominent and slightly thicker AML at a low-altitude site in south China than at a high-altitude site on the Tibetan Plateau (He et al., 2021). This was attributed to a higher aggregation rate above the AML and slower-falling particles at the low-altitude site. The higher AML height at this site, confirmed by MRR's DSD profile, was associated with a more active breakup process below the AML, while coalescence process dominated at the high-altitude site (He et al., 2021).

3.3.2. Temporal variation

Long-term (2009–2019) MRR observations in Kolkata, India, showed that AML height typically peaked between 12:00 and 16:00, corresponding to surface temperature maxima. This diurnal pattern was more pronounced for the warmer pre-monsoon season (Saha et al., 2023), when 80 % of stratiform events occurred outside peak temperature hours (51 % for the monsoon). In contrast, AML thickness at this site showed minimal diurnal and seasonal variations (Saha et al., 2023).

3.4. Event type classification

Quite a few of the reviewed studies explored MRR's utility in verifying rainfall event type, using various methods, typically based on surface observations. These methods rely on rainfall rate, DSD, brightness temperature, electric field (EF), Z–R relations, and isotherms, each discussed below.

3.4.1. Rainfall rate

MRR-derived AML data can validate event type classification based on surface rainfall rate (e.g., Wang et al., 2021). For instance, events with (without) a BB signature were used to confirm stratiform (convective) events defined as rainfall periods of 10-min or longer with intensity <10 mm/h ($\geq$ 10 mm/h). Shorter periods were classified as transition or mixed types (Sreekanth et al., 2019).

3.4.2. DSD

More refined classifications used DSD (Ghada et al., 2022), with a higher concentration of large drops typically indicating convection (Majumder et al., 2015; Wang et al., 2021). However, DSD varies across location and time. For example, large-drop dominance was observed in southwest vs. northeast monsoons (Narayana Rao et al., 2009), and in nocturnal vs. diurnal equatorial rains (Ramadhan et al., 2020). Weaker diurnal BB signatures were linked to riming (vs. aggregation) (Ramadhan et al., 2020). In Kolkata, AML heights of 5.0–5.5 km were associated with mean drop diameter $\geq$ 1.2 mm, while smaller drops corresponded to broader variability (3.9–5.5 km) (Saha et al., 2022). Given such complexities, event classification benefits from simultaneous analysis of surface DSD and MRR profiles (Raut et al., 2021).

3.4.3. Brightness temperature

Brightness temperature patterns from RPG-HATPRO, as a passive multifrequency radiometer, offers clues to event type. Stratiform and convective events showed higher temperatures at 22.2 GHz and 31.4 GHz, respectively (Halder and Maitra, 2020). The former frequency is more vapor-sensitive while the latter is more LWC-sensitive. A limitation is scattering during heavy rain, which reduces brightness temperature at all frequencies.

3.4.4. Electric field (EF)

An electric field mill is a surface instrument that detects EF changes induced by clouds, aiding in the early identification of event type. A sharp drop in EF strength approximately 30 min before the onset of rainfall is a typical signature of impending convection (Halder and Maitra, 2020). During rainfall, stronger EF values have been associated with convective events, and weaker values with stratiform ones (Sreekanth et al., 2019).

3.4.5. Z–R relations

At a coastal site in India, MRR analysis revealed distinct Z–R relations for BB and non-BB events, consistently throughout the vertical profile and even near the surface (Rajasekharan Nair, 2020). Hence, ground-based Z and R data obtained from a disdrometer provide proxies for event type classification. However, Z–R equations significantly vary by latitude (Rajasekharan Nair, 2020) and month (Mehta et al., 2020; Rajasekharan Nair, 2020). A collocated MRR can assist calibrations for a given climate.

3.4.6. Isotherm heights

Radiosonde temperature profiles helped identifying additional event types, such as “low level” precipitation where the 0 °C isotherm lies above the MRR echo top (Cha et al., 2009). For convective storms, the echo top may range between -5 °C and $+5$ °C, placing strong reflectivity peaks well above the 0 °C isotherm. While MRR's dual BB signatures are usually interpreted as mixed stratiform–convective events or transition between two events (Das et al., 2010), ground-classified mixed events may occur during periods without BB aloft (Wang et al., 2021).

4. Discussion

This section discusses the key strengths and limitations of MRR in AML studies and highlights opportunities to address those in future work.

4.1. Frozen particles and snow observations

Frozen, liquid, and mixed precipitation particles with different dielectric properties and fall velocities are measurable by Doppler radar. DSD retrievals typically assume spherical raindrops, limiting their accuracy for irregularly shaped particles such as snowflakes. Equivalent DSD for such particles can be achieved through bias correction schemes if snow and rain layers are identified in the atmosphere. Then, new relationships between MRR observations above and below the AML can be fitted (Cao et al., 2023; Cha et al., 2009; Rawat et al., 2022). A velocity threshold (e.g., > 3 m/s for rain) may also distinguish rain from snow (Shates et al., 2023).

The fall velocity profile from MRR may even distinguish between particles with variable densities. Radial velocity from WRs scanning at small elevation angles is influenced by horizontal wind. However, MRR may record higher fall velocities for snow aloft than for rain in a lower elevation (Cao et al., 2023), due to convective downdrafts. Incorporating wind data, from collocated wind profilers or reanalysis datasets, may help interpreting strange MRR profiles. In addition, wind impacts on AML microphysics such as melting and coalescence rates can be considered.

In mixed-phase conditions, MRR signals may appear similar across diverse snow–rain balances, which complicates the interpretations. Recent findings using multifrequency radar profiles and dual-wavelength ratios (Dias Neto et al., 2019) suggest diverse particle populations in cold clouds, supporting the use of combined sensor platforms for improved classifications.

4.2. Quality control and consistency check

Reflectivity is central for AML detection, but, like other remote sensing data, MRR reflectivity measurements are prone to errors and the affected profiles, particularly during non-stratiform events lacking a BB signature, should be excluded or treated differently.

Therefore, reliable event-type classification methods are desirable. Notably, plotting the relative frequency of event types against near-surface reflectivity (Cha et al., 2009) revealed meaningful patterns that warrant further investigation using integrated MRR, radiosonde, and disdrometer data.

The lowest few range gates of MRR, typically up to 200 m, are often unusable due to noise and ground clutter (Benarroch et al., 2022), and, thus, can be removed before deriving AML.

4.3. AI modeling

As mentioned earlier, some assumptions underlying MRR variables—such as the use of Rayleigh reflectivity and rain rate formulas—are not valid for frozen or mixed-phase hydrometeors. However, AI models capable of capturing complex, nonlinear relationships may still infer AML features from the MRR variables. It is especially advisable to incorporate auxiliary inputs such as Doppler velocity, along with reflectivity. Hybrid approaches can benefit from integrating vertical profiles from other sensors such as DWRs (Chellini et al., 2022; Dias Neto et al., 2019) to account for variability between Rayleigh and non-Rayleigh scattering conditions.

A major limitation of the deep learning model by Brast and Markmann (2020) lies in its labor-intensive data preparation, and, thus, time-consuming evaluations. The visual inspections used in this approach might be challenging during unstable or rapidly evolving AML conditions. For broader applicability, more systematically curated training and testing datasets, automatically validated with multiple sources, are needed to generalize the model across varying scenarios.

Heavy rainfall can cause significant attenuation of MRR signals, requiring temporal gap-filling. This may be addressed by training models on long timeseries of profiles, where AML heights from adjacent time steps can be used as predictive features.

Sensitivity analyses by Brast and Markmann (2020) showed that models trained on 10-s and 25-m resolution data retained reasonable performance when scaled up to 1-min and 100-m resolutions. That being said, new AI models trained on other resolutions might have other ranges of viable applicability.

4.4. Detection range

MRR's detection range is limited compared to instruments such as a multi-level scanning WR or other FMCW radars (Zhu et al., 2022b). For instance, the average AML height in Beijing during April–September 2010 ranged between 3700 and 5000 m (Huang et al., 2013), which may exceed MRR's vertical coverage depending on setup.

Peak reflectivity heights also vary seasonally, often being lower during winter. Because of the trade-off between range and resolution in MRR configurations, the vertical resolution may be optimized seasonally and geographically. Despite these limitations, MRR profiles even below AML can still support valuable applications, such as classifying event types (stratiform, convective, etc.) based on DSD (Halder and Maitra, 2020).

Additionally, consistent MRR measurements at mid-level heights (i.

e., above clutter area) may provide strong input for automated machine learning method, a potential that remains underexplored in the literature (Ghada et al., 2022).

4.5. Mobile setup

AML observations remain limited due to the scarcity of long-term in-situ measurements. Mobile field campaigns by temporary deploying an MRR at several locations offer a practical solution. These campaigns can help fill spatial and temporal gaps, particularly in regions or seasons with limited data, especially useful for snowmelt hydrology in remote or data-sparse catchments.

Given seasonal variability in AML height, multi-month deployments can generate reference values for expected AML levels. Repeating mobile MRR deployments across different locations and seasons can support regionalization of MRR and enhance higher-resolution AML modeling.

4.6. Single polarization

A distinct peak in LDR is indeed a key AML signature for dual-polarization observations. However, MRR's single polarization design limits its ability to capture such signature linked typically to wetted, asymmetric snowflakes (Di Girolamo et al., 2012; Di Girolamo et al., 2009; Schuur et al., 2014).

Incorporating multiple polarimetric variables can improve interpretation of AML microphysical processes particularly regarding hydrometeor size and concentration (Xie et al., 2016a). However, LDR can be weak for hail compared to snow (Kumjian et al., 2022). In such cases, MRR's fall velocity profile may still offer additional discrimination capability.

4.7. Non-Rayleigh scattering

Non-Rayleigh scattering can occur even at K-band frequencies. As a result, the reliability of AML algorithms based on MRR may vary depending on the maximum drop size in the observed DSD.

While LWC profiles are not commonly used for AML detection, they can support attenuation-based precipitation retrievals due to their lower sensitivity to DSD (Chen et al., 2023). Additionally, MRR-derived parameter such as spectral width, skewness, and kurtosis, which reflect variability in fall velocity (Garcia-Benadi et al., 2020), could be combined with LWC data to avoid AML detection during periods without rainfall.

4.8. Long-term evaluation, and climate change

Given the seasonal variability of AML height, long-term evaluations based on 2D histograms or CFADs are more informative when analyzed by season or month. While CFADs have been used to assess different DSDs, further insights may be achieved with dedicated analysis of each event type (e.g., convective, stratiform, or mixed), or precipitation phase (e.g., snowfall and rainfall).

Although AML height and structure are known to vary with near-surface weather conditions (Fehlmann et al., 2018; Hosseini et al., 2023b), a gap remains in understanding how AML trends evolve with climate change. Under global warming, precipitation processes and AML patterns are mutually affected. This can cause a wide range of environmental consequences from changes in the phase, intensity, and other qualities of precipitation over land and oceans. Future research could, therefore, integrate long-term MRR observations and their relation to surface weather parameters with projected climate scenarios to explore potential shifts in AML characteristics and their impact on precipitation under changing climate conditions.

4.9. Uncertainty quantification

While this review highlights methodological advancements and comparative analyses of AML detection using MRR, a systematic quantification of measurement uncertainty remains largely unaddressed in the current literature. Variability can arise from factors such as attenuation effects, signal aliasing, instrument calibration, and environmental influences (e.g., wind, clutter). Uncertainty propagation is particularly relevant when integrating MRR data with complementary sensors or when using outputs for hydrological or climate modeling. However, comprehensive error characterization requires harmonized datasets with known reference standards, which are often unavailable. Future studies should focus on developing standardized uncertainty assessment frameworks.

5. Concluding remarks

This review underscores MRR's contributions to AML studies, particularly in providing high-resolution, continuous profiling of precipitation microphysics. MRR has been instrumental in addressing observational gaps in diverse regions, but opportunities remain to enhance its utility.

MRR's observations can be strengthened through integration with multi-sensor data, leveraging complementary instruments like dual-polarization radars, radiosondes, and satellites. This approach mitigates MRR's limitations, such as single-polarization design, and enables more robust AML detection methods when combined with reanalysis datasets and AI modeling, e.g., by incorporating dual-wavelength ratios instead of dual-polarization variables. The use of AI could extend automated AML detection, provided standardized training datasets and auxiliary variables, such as wind profiles.

Expanding mobile MRR deployments can fill critical data gaps in under-observed regions, such as oceans or remote mountains, improving regionalization of AML profiles for enhanced hydrological applications or satellite signal processing. Further research into AML microphysics, non-Rayleigh scattering effects, and underutilized variables like LWC will refine precipitation retrievals and support broader scientific goals.

Collaboration among researchers and professionals to share AML datasets and methodologies and develop generalizable methods based on the national weather radar systems, coupled with emerging international satellite missions (e.g., EarthCARE), offers a pathway to global advancements. In this review we discussed different potentials of various instruments used with MRR for studying AML. With progressing learning abilities of AI models and dedicated methods for preparing training datasets via MRR or other radar profilers, future research can leverage even more sources such as polar-orbiting meteorological satellites (JPSS and MetOp) with vertically resolved temperature, humidity, and cloud property data.

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Authors contribution

- The conception and design: Hasan Hosseini with help of other authors
- The data acquisition/analysis/investigations, i.e., reviewing the literature and collecting relevant information from them: Hasan Hosseini, Hossein Hashemi, Jonas Olsson, Søren Liedtke Thorndahl, Bengt Rydberg, Ronny Berndtsson
- Writing the first draft and visualizations: Hasan Hosseini with help of other authors
- Critical review and revising the manuscript: All authors

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.atmosres.2025.108307>.

Data availability

MRR and X-band radar data used in Fig. 7 of the article were provided by the Swedish water utility VA Syd.

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