

Response to Reviewers' Comments

Reviewer #1:

'Comment on egusphere-2026-1091'.

General Comments

This manuscript presents a comprehensive analysis of cloud vertical structure (CVS) across China using a national network of 80 MMCRs for the year 2024. The authors develop an improved CVS retrieval algorithm that incorporates height-dependent radar sensitivity and variance-based clutter suppression. They systematically characterize the spatial, seasonal, and diurnal variations of CVS metrics (cloud base height, cloud top height, cloud thickness, and cloud layer number) and quantify the regulatory effects of thermodynamic (lower-tropospheric stability, specific humidity at 850 hPa), dynamical (wind shear at 700 hPa), and land-surface factors. The findings provide valuable observational benchmarks for evaluating and improving cloud parameterization schemes in weather and climate models. Overall, the manuscript is well written and the concepts are clearly presented. However, several major and minor issues require further improvement. Therefore, I recommend that the authors revise their manuscript to address the following comments.

Response: We thank the reviewer for his/her comprehensive evaluation and thoughtful comments, which help tremendously to improve the quality of our work. We have tried our best to address the reviewer's concerns one by one.

Per your kind suggestions, a series of revisions have been implemented, including streamlining the discussion of cloud thickness to eliminate redundancy, adding concise descriptions of supplementary Figures S3 and S4, and improving figure consistency to enhance the overall quality of the manuscript. We have also revised several potentially absolute statements to more rigorous wording and clarified the spatial scale mismatch between ERA5 reanalysis and MMCR point-based observations as a potential limitation. For more details, please refer to the revision manuscript.

For clarity purpose, here we have listed the reviewer's comments in **black**, followed by our responses in **blue**, and the modifications to the manuscript are in *italics*. We sincerely hope that the reply and the revisions can satisfy the reviewer's expectations.

Major Comments

1. The discussion of cloud thickness (CT) appears in Sections 3.5.3 (single-factor correlations) and 3.6.3 (bivariate analysis). While both add value, some redundancy exists. Consider streamlining the single-factor section to focus on broad patterns and reserving detailed interaction effects for the bivariate section.

Response: We agree with the reviewer that there was some overlap between the single-factor and bivariate discussions of cloud thickness (CT). In the revised manuscript, we have carefully streamlined the single-factor section (now Section 3.5.3) to focus on the dominant annual correlation patterns and their spatial characteristics. All detailed interaction effects, conditional responses, and combined constraints are now exclusively presented and discussed in the bivariate analysis (joint dependence on paired variables, Fig. 13).

Specifically, in the single-factor section, we have removed extended physical interpretation that duplicated the bivariate discussion, condensed the description of seasonal modulation to a single sentence per variable, keeping only the range of seasonal station percentages as supporting evidence, and shifted the mechanistic explanation of conditional behavior (e.g., why moisture alone is insufficient to guarantee thick clouds) entirely to the bivariate section.

As a result, the single-factor section now concentrates on what the broad patterns are, while the bivariate section addresses how the factors jointly constrain CT. We believe this revision eliminates redundancy and makes the logical flow clearer. The text about cloud thickness was revised in the revised manuscript, as follows (Lines 688–743):

“3.5.3 Impact of atmospheric thermal and dynamical factors on CT

Cloud thickness exhibits distinct correlation patterns that differ from those of CBH and CTH (Fig. 12). For q_{2m} (Fig. 12a), positive correlations dominate across 71.3% of stations, indicating that abundant low-level moisture favors vertically extended clouds. This relationship is pronounced over southern China and the eastern Tibetan Plateau margins, where active moist convection prevails. Higher specific humidity sustains positive buoyancy over deeper layers, promoting thicker clouds (Johnson et al., 1999; Holloway and Neelin, 2009). Negative correlations (28.7% of stations), scattered over arid northwestern China and parts of Inner Mongolia, may reflect environments where moisture is insufficient to support deep convective development. Seasonal composite analyses (Fig. S8 a-d) show that this positive coupling is most widespread in summer (71.3%) and weakest in autumn (40.0%), confirming the strong but seasonally modulated link between moisture and cloud vertical extent.

For LTS_{surf} (Fig. 12b), cloud thickness shows a nearly equal split between positive and negative correlations (50% of each), with a spatially heterogeneous,

intermingled pattern across China rather than any dominant geographic signature. This mixed pattern reflects the dual role of thermodynamic stability in cloud development. On one hand, enhanced stability (e.g., strong temperature inversions) typically suppresses convective development, leading to negative correlations. On the other hand, stable stratification can favor the maintenance and thickening of stratiform clouds trapped beneath the inversion layer, especially under sustained moisture supply, thereby yielding positive correlations (Klein and Hartmann, 1993; Wood and Bretherton, 2006). Critically, seasonal composite analyses (Fig. S8 e-h) reveal that positive correlations dominate in summer (76.3%), when extensive stratiform cloud decks associated with the East Asian summer monsoon are prevalent, while the other seasons remain near parity. This seasonal contrast directly supports the interpretation that the sign of the CT – relationship is governed by the prevailing cloud type and moisture regime, rather than by stability alone.

Cloud thickness shows a predominantly negative correlation with VWS (73.9% of stations; Fig. 12c), indicating that stronger vertical wind shear generally suppresses vertical cloud development. Negative correlations are widespread across southern China, the Tibetan Plateau margins, northeastern China, and the North China Plain. Positive correlations (26.1% of stations), scattered across limited areas of northwestern China, may reflect environments where moderate shear organizes convection into longer-lived systems capable of greater vertical development consistent with the "optimal shear" concept (Weisman and Rotunno, 2000). Seasonally (Fig. S8 i-l), negative correlations are most widespread in winter (65.0%) and spring (61.4%), and least so in summer (41.3%), suggesting that the suppressing effect of shear on cloud thickness is more pronounced when deep convection is less frequent, while in summer, organized convective regimes may partially offset this suppression (Weisman and Rotunno, 2000; Houze, 2018).

CT exhibits distinct joint-dependence characteristics that integrate the controls on both cloud-base and cloud-top environmental processes. For the q_{2m} - LTS_{surf} combination (Fig. 13a), the thickest clouds occur under high specific humidity combined with high lower-tropospheric stability. This indicates that under high-humidity conditions, stronger stable stratification does not necessarily suppress cloud thickness; rather, it can support the accumulation of thick stratiform cloud layers beneath the inversion by trapping moisture within a confined boundary layer, thereby yielding considerable geometric thickness (Klein and Hartmann, 1993; Wood and Bretherton, 2006).

For the LTS_{surf} -VWS combination (Fig. 13b), the maximum CT occurs under moderate LTS_{surf} and moderate vertical wind shear. Both excessively high LTS_{surf} and intense shear markedly reduce cloud thickness. High LTS_{surf} strongly

suppresses deep convection, whereas intense shear enhances turbulent entrainment at the cloud top and disrupts organized updraft structures, thereby limiting vertical growth. In contrast, the combination of moderate stability and moderate shear provides conditions that are favorable for organizing cloud systems and allowing greater vertical development, without being overly constrained by either extreme stability or excessive turbulence (Weisman and Rotunno, 2000).

For the q_{2m} -VWS combination (Fig. 13c), CT increases primarily with humidity. Under low-humidity conditions, CT remains uniformly small regardless of shear intensity. Under high-humidity conditions, however, CT tends to increase with wind shear up to moderate–strong values. This indicates that moisture availability is the fundamental precondition for thick clouds, while moderate to strong shear can further enhances the vertical extent of moisture-rich air masses by modulating cloud organization and dynamic mixing. Collectively, these joint results confirm that moisture acts as the dominant driver for deep cloud systems, while stability and shear functions as strong regulators that either suppress or facilitate vertical development depending on their specific magnitudes.

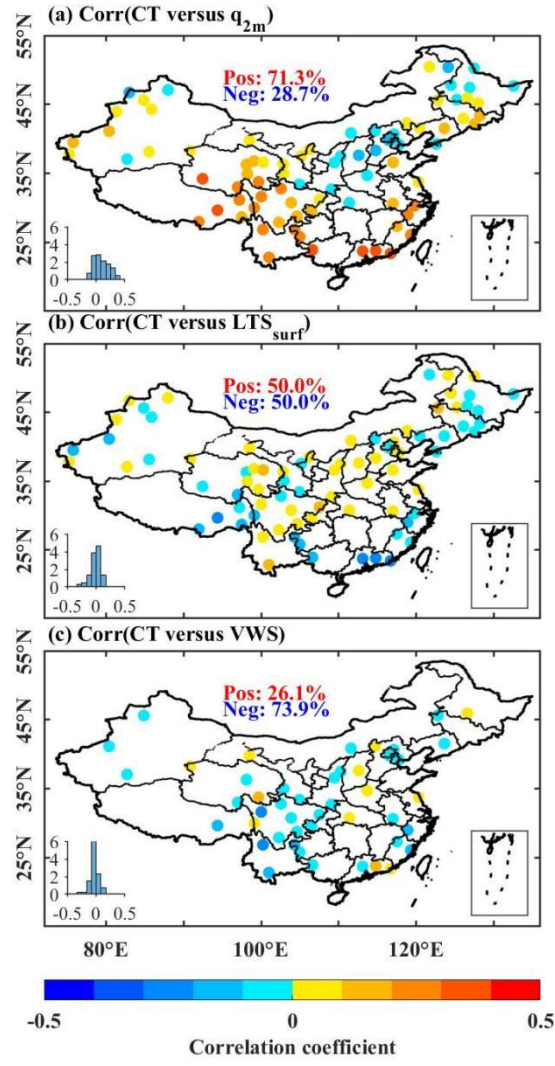


Figure 12. Similar as Figure 8, but for CT.

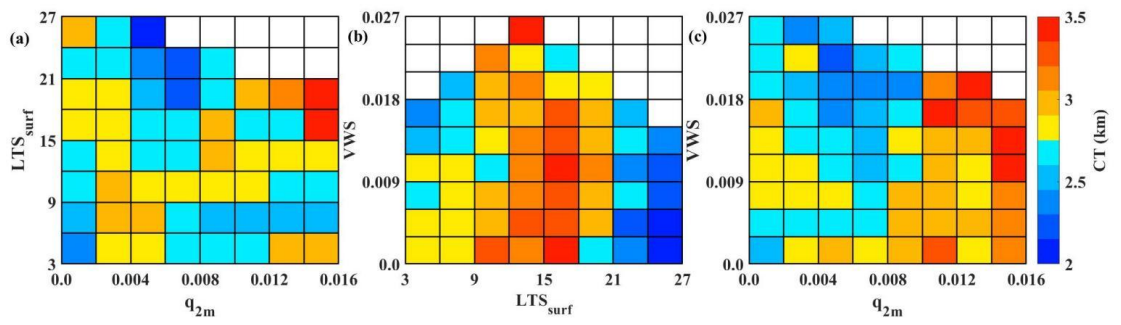


Figure 13. Similar as Figure 9, but for CT.

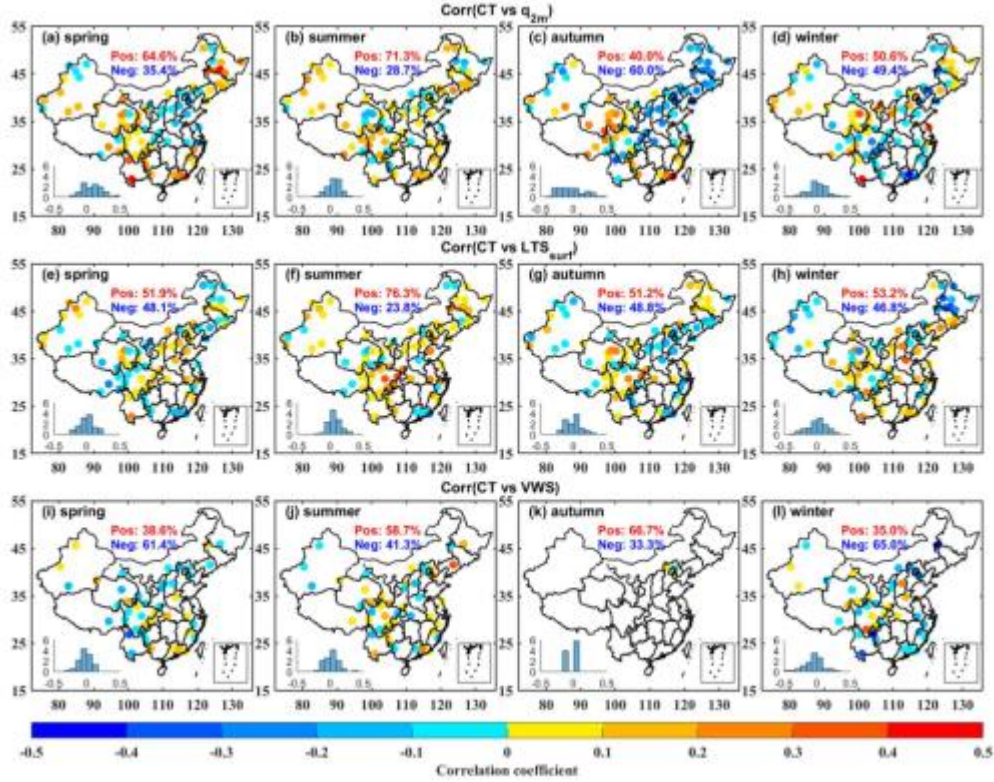


Figure S8. Similar as Figure S6, but for CT. ”

Similar revision also has been done for CBH and CTH. Please see the details in the revised manuscript.

2. Supplementary figures (S2, S3) are mentioned but not described in the main text. Please add a brief summary of their key patterns (e.g., seasonal CTH and CT distributions) to make the main text more self-contained.

Response: We have added concise descriptions of the key spatial patterns shown in Figures S3 (seasonal CTH distribution) and S4 (seasonal CT distribution) in the revised version within Section 3.2. The revised text is provided below.

“CTH exhibits similar seasonal variability (Fig. S3), with mean values of 7.51 ± 1.00 km in summer, 6.37 ± 0.93 km in spring, 5.70 ± 0.71 km in autumn, and 4.70 ± 1.33 km in winter. As shown in Fig. S3, summer CTH exceeds 8 km over much of eastern China (especially in the south) but remains below 6 km over the Tibetan Plateau. However, this east–west contrast diminishes in winter, when CTH is low (generally 3–5 km) across most of the country. The higher summer CTH reflects enhanced convective instability and stronger vertical development, whereas wintertime stability limits cloud growth largely to the lower troposphere. Regionally, CTH over the Tibetan Plateau is systematically lower than over eastern China. This finding is consistent with Chen et al. (2017), who reported that deep convective

clouds over the Plateau are approximately 20 – 30% thinner than those over eastern China, and with Luo et al. (2011), who noted that convection over the Plateau is generally shallower and less frequent. The reduced vertical extent may be related to weaker large-scale dynamical forcing and frequent weak upward motion over the Plateau (Chen et al., 2017).”

“CT follows a seasonal cycle similar to that of CTH, with mean values of 3.56 ± 0.72 km in summer, 3.13 ± 0.49 km in spring, 2.93 ± 0.47 km in autumn, and 2.56 ± 0.72 km in winter (Fig. S4). *In summer, the thickest clouds (~4 km) occur over southern China and the eastern Tibetan Plateau margins, whereas winter clouds are uniformly thin (~2 km) across the country. The spatial pattern of CT largely follows that of CTH, indicating that thicker clouds are primarily associated with higher cloud tops rather than lower bases.* The larger CT during summer reflects the combined effects of enhanced instability, deeper convective development, and increased moisture availability, while the thinner winter clouds are consistent with suppressed vertical growth under stable atmospheric stratification.”

3. ERA5 represents large-scale atmospheric conditions at 0.25° resolution (~31 km), whereas MMCR observations are point-based. The mismatch in spatial scales may introduce uncertainties, particularly in regions with complex terrain or strong local gradients. Please add a brief discussion of this limitation.

Response: We thank the Reviewer for this suggestion. We fully agree that the spatial scale mismatch between ERA5 (~31 km) and point-based MMCR observations may introduce uncertainties, particularly over complex terrain. In the revised manuscript (Section 2.2.3), we have added a discussion acknowledging this limitation. We also performed a sensitivity test using the higher-resolution ERA5-Land (0.1°), which confirmed that the key correlation patterns are robust to grid resolution (Supplementary Figs. S5). The added text reads (Lines 241-252):

“A spatial scale mismatch inevitably exists between the gridded ERA5 fields (~31 km) and the point-based MMCR observations, which may introduce uncertainties over complex terrain and regions with strong surface heterogeneity. To evaluate the sensitivity of our results to this mismatch, we repeated the key correlation analyses using ERA5-Land ($0.1^\circ \times 0.1^\circ$, ~9 km), which better resolves near-surface variability. The comparison (Figs. S5) shows that the correlation signs, spatial patterns, and magnitudes are highly consistent between the two products, confirming that our conclusions are not sensitive to the specific grid resolution. While some local-scale uncertainty is inherent in any point-to-grid comparison, the consistent spatial patterns across diverse climatic and topographic settings indicate that the identified relationships reflect robust large-scale physical mechanisms. The procedure for

temporally aggregating the MMCR observations and matching them with ERA5 is described in Section 2.3.”

Minor Comments

4. Lines 117-120: Introduction. The statement “no previous study has ever provided a national-scale, high-frequency characterization of CVS across China using a coordinated ground-based radar network” may be overly absolute. Please revise it.

Response: We have revised the description to a more rigorous and objective version, as follows (Lines 115-118):

“Despite these advances, most studies have focused on isolated factors or localized regions. To our knowledge, a national-scale, high-frequency characterization of CVS across China based on a coordinated ground-based radar network remains lacking, and the combined thermodynamic, dynamical, and land-surface controls have yet to be systematically quantified.”

5. Line 348, Section 3.2 paragraph 2: "favouring higher cloud bases." → "favoring" (consistent with American English spelling used throughout the manuscript).

Response: Done as suggested.

6. Reference list: Slingo, J. M. (2007) → The year in the text (Slingo, 1987) does not match the reference year; please correct the reference or the in-text citation.

Response: We thank the reviewer for pointing out this inconsistency. Upon checking, the correct publication year of Slingo’s classic paper on the cloud prediction scheme for the ECMWF model is indeed 1987, not 2007. Therefore, we have corrected the reference list entry from “2007” to “1987” to match the in-text citation. The correction has been made in the corresponding location in the main text as follows:

Slingo, J. M.: The development and verification of a cloud prediction scheme for the ECMWF model, *Quart. J. Roy. Meteor. Soc.*, 113, 899–927, <https://doi.org/10.1002/qj.49711347710>, 1987.

7. The term “lifting condensation level (LCL)” is used multiple times in the text. After its first definition, please use only “LCL” thereafter to avoid repetition.

Response: Done as suggested.

8. Figure 3. Please unify the longitude range in Figure 3 with that in the other figures.

Response: Corrected as suggested. The corrected figure is as follows,

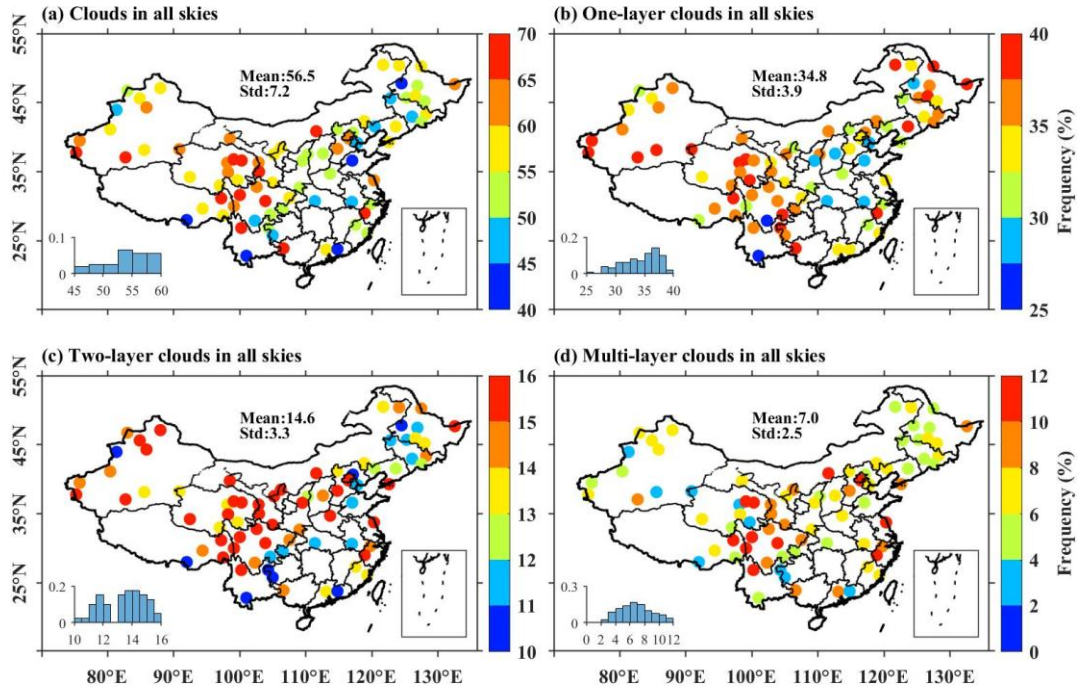


Figure 3. Spatial distribution of annual mean cloud occurrence frequency for different cloud layering classifications: (a) all clouds, (b) single-layer clouds, (c) two-layer clouds, and (d) multi-layer clouds (three-, four-, and five-layer clouds) under all-sky conditions in 2024. The data is derived from the 80 MMCR stations presented in Figure 1. Notably, the color bars are scaled independently across panels to improve visual clarity. In addition, each panel shows the histograms depicting the probability distributions of cloud occurrence frequencies, with the corresponding mean values and standard deviations also presented for each distribution.

9. Figure 15. The MMCR has been defined in Figure 1 already. Therefore, you do not need to define it here.

Response: The caption was corrected as follows (Lines 1350 to 1355),

“Figure 15. Schematic diagram showing (a) the national *MMCR* network across China in 2024, (b) the vertical distribution of cloud occurrence frequency in summer (red) and winter (blue), and (c) the key controlling factors (thermodynamic, dynamical, and land-surface) of the CVS. Upward and downward arrows indicate increases and decreases, respectively, in panel (c).”

10. In Section 3.7, “afternoon single-layer clouds” are defined as those occurring during peak daytime heating, but the exact time window is not specified. Please define “afternoon” (e.g., 1400–1800 LT) explicitly to ensure reproducibility.

Response: In the revised manuscript, we have explicitly defined the time window for “afternoon single-layer clouds” as 1400–1800 LT. Accordingly, we revised this sentence as follows:

“To quantify land-surface influences, we compare CBH across land cover types under two conditions: (i) *all-hour low clouds* and (ii) *afternoon (1400-1800 LT) single-layer low clouds* (Fig. 14). ”

11. Line 651-668: There is a numbering error: “3.7.1 All-cloud conditions” is followed by “3.7.1 Afternoon single-layer clouds.” The second subsection should be numbered “3.7.2.” Please correct.

Response: Corrected as suggested.

Reviewer #2:

'Comment on egusphere-2026-1091'

General Comments

This paper uses one year of observations from a newly established national Ka-band cloud radar network to characterize cloud vertical structure across China, including cloud occurrence, layer number, CBH, CTH, and CT, and further relates these properties to humidity, lower-tropospheric stability, wind shear, and land cover. The dataset is clearly valuable, especially because the 1-min temporal resolution and 30-m vertical resolution allow the authors to examine seasonal and diurnal variations that are difficult to resolve from satellites or radiosondes. The paper's main contribution is therefore not only the national-scale description of cloud vertical structure, but also the attempt to connect these observed structures with thermodynamic, dynamical, and land-surface controls. Overall, the study has strong observational potential and could provide useful benchmarks for model evaluation, but several issues need to be addressed before the physical conclusions can be considered fully convincing.

Response: We thank the reviewer for his/her comprehensive evaluation and thoughtful comments, which help tremendously to improve the quality of our work. We have tried our best to address the reviewer's concerns one by one.

Per your kind suggestions, substantial changes have been made, including adding more critical references on the topic analyzed here, complementing the lower-tropospheric stability (a metric for atmospheric stability), streamlining the text, more in-depth discussion and result interpretation, among others. For more details, please refer to the revised manuscript.

For clarity purpose, here we have listed the reviewer's comments in black, followed by our responses in blue, and the modifications to the manuscript are in italics. We sincerely hope that the reply and the revisions can satisfy the reviewer's expectations.

Specific Comments:

1. One limitation is the short time period. All major statistics are based on 2024, but the manuscript often presents the results as a national-scale benchmark. Cloud vertical structure over China can be strongly affected by monsoon variability, large-scale circulation anomalies, regional drought or wet conditions, and unusual synoptic patterns in a given year. The authors may discuss how representative 2024 is, for example by comparing cloud fraction, precipitation, humidity, stability, or circulation conditions with multi-year satellite or reanalysis records.

Response: We sincerely thank the reviewer for raising this insightful and critical comment regarding the representativeness of our single-year dataset. We fully agree that a single year of observations cannot constitute long-term climatology, and we

have addressed this concern from three perspectives: (i) justification for selecting 2024, (ii) a quantitative representativeness assessment using ERA5 reanalysis, and (iii) tempered language throughout the revised manuscript.

(1) Why 2024 was selected

Prior to 2024, fewer than 30 MMCRs were operational across China, which was insufficient for reliable national-scale analysis of cloud vertical structure (CVS). In 2024, the network underwent a major expansion to nearly 120 stations, of which 80 met our strict data-quality criterion (≥ 100 valid observation days per year, defined as calendar days with at least 8 hours of valid MMCR measurements). Thus, 2024 represents the first year in which a sufficiently dense observing network became available, making it the only feasible foundation for this pioneering investigation. This justification has been added to Section 2.1.1 of the revised manuscript, as follows:

“MMCR data have been widely used in cloud boundary detection (e.g., Zhang et al., 2017; Zhou et al., 2019; Fang et al., 2023) and exhibit strong consistency with radiosonde observations (Wang et al., 2016; Zhao et al., 2017; Chen et al., 2022). In this study, MMCR data for the year of 2024 were obtained from the China Meteorological Administration (CMA). Of the 120 MMCR stations operating across China in 2024, only those with at least 100 valid observation days annually (*defined as calendar days with at least 8 hours of valid MMCR measurements*) were retained to ensure data quality. This criterion resulted in the selection of 80 stations for subsequent analysis (Fig. 1). *Notably, we selected 2024 because it was the first year in which the MMCR network achieved sufficient density for national-scale analysis. Before 2024, fewer than 30 stations were operational nationwide, which was inadequate for a robust spatial characterization of CVS. The major expansion in 2024, with nearly 120 MMCRs deployed, made this pioneering investigation feasible. Even though this single-year dataset does not constitute a long-term climatology, it provides the first observationally dense and vertically resolved national snapshot of CVS across China.*”

(2) Representativeness of 2024 relative to the past decade

Following the reviewer's suggestion, we evaluated the representativeness evaluation of 2024 using ERA5 reanalysis data for 2014 to 2023 as the climatological baseline. We calculated standardized anomalies (Z-scores) of annual mean total cloud cover, precipitation, and 2 m specific humidity (q_{2m}) in 2024. A Z-score within ± 2 is generally considered to reflect typical interannual variability. The key results are summarized in Figure R1 (provided below for the reviewer's reference only), as follows,

Total cloud cover: The ERA5-derived annual mean cloud cover for 2024 is 54.54%, nearly identical to the 2014–2023 climatological mean of 54.05% (relative deviation 0.9%, Z-score well below 1.0). This indicates that the overall cloud cover in 2024 falls well within the range of natural interannual variability, and that our MMCR-derived cloud occurrence statistics are not unduly influenced by anomalous cloud cover. This supports the reliability of the CVS metrics (CBH, CTH, CT) derived from the 2024 observations.

Precipitation: The Z-score for annual mean precipitation in 2024 is 1.8, indicating a notably wetter-than-normal year.

Low-level moisture: 2024 shows a pronounced positive anomaly in q_{2m} , with a Z-score of 3.5, representing an exceptionally high value relative to the past decade.

Rather than undermining our conclusions, these anomalous moisture and precipitation conditions provide a valuable “natural experiment” that reinforces the physical mechanisms proposed in our study. As we demonstrate in Section 3.5, enhanced low-level moisture promotes deeper vertical cloud development. The anomalously high precipitation in 2024 is consistent with this enhanced moisture-driven convection, and it aligns with our observed elevated cloud top heights and cloud thickness under humid conditions. In other words, 2024 exhibited near-normal cloud frequency but extreme low-level moisture—exactly the combination that our core argument predicts: moisture availability primarily controls the vertical extent of clouds once they form, rather than their occurrence frequency. Therefore, the CVS–thermodynamic relationships we derive are not artifacts of an anomalous year; rather, they are physically consistent and likely conservative relative to drier years.

We acknowledge that the single-year nature of the dataset precludes definitive multi-year climatological conclusions. We have therefore adopted a cautious tone throughout the manuscript, replacing absolute statements with precise wording such as “first observational assessment for 2024” and “an unprecedented snapshot.” In the Abstract and Conclusions, we explicitly state that this record provides a baseline for future multi-year evaluations rather than long-term climatology.

(3) Specific textual revisions

We have revised the Abstract as follows:

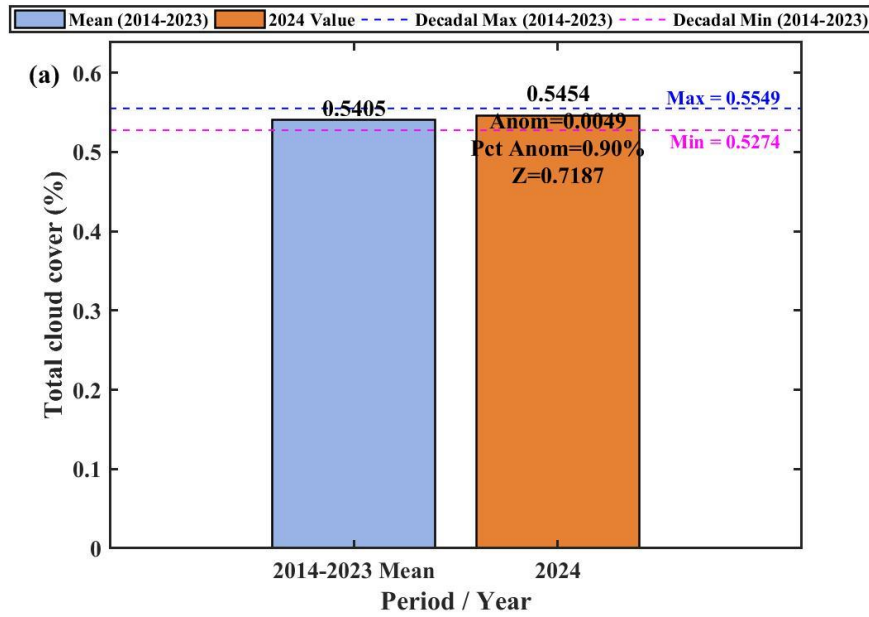
“Using a newly established national network of 80 Ka-band millimeter-wave cloud radars (MMCRs), *here we present a high-spatiotemporal-resolution (vertical resolution of 30 m, temporal resolution of 1 min) characterization of CVS across China based on one year (2024) of observations*, and quantify its thermodynamic, dynamical, and land-surface controls.”

In the Summary and Conclusions, we now state:

“This study presents the first national-scale, high-spatiotemporal-resolution *analysis* of CVS across China based on observations from a coordinated network of 80 Ka-band cloud radars *during 2024, providing an unprecedentedly detailed snapshot (30 m vertical, 1 min temporal resolution) of cloud vertical structures and their governing factors.*”

“Overall, this study provides a high-resolution, observationally constrained snapshot of cloud vertical structure across China and establishes a quantitative framework linking CVS metrics to thermodynamic, dynamical, and land-surface controls (Figure 15). ... *Although this one-year record does not support long-term trend analysis, it establishes a robust baseline against which model-simulated CVS can be evaluated across timescales, especially when combined with multi-year satellite or reanalysis products, thereby supporting iterative improvement of cloud schemes and enhancing prediction skill from weather to climate scales. Future work should extend this analysis to multi-year datasets to assess interannual variability and explore the role of CVS in extreme weather events and regional climate feedbacks.* ”

We believe these revisions and the accompanying analysis adequately address the Reviewer’s concern. We are grateful for the suggestion, which has significantly strengthened the manuscript.



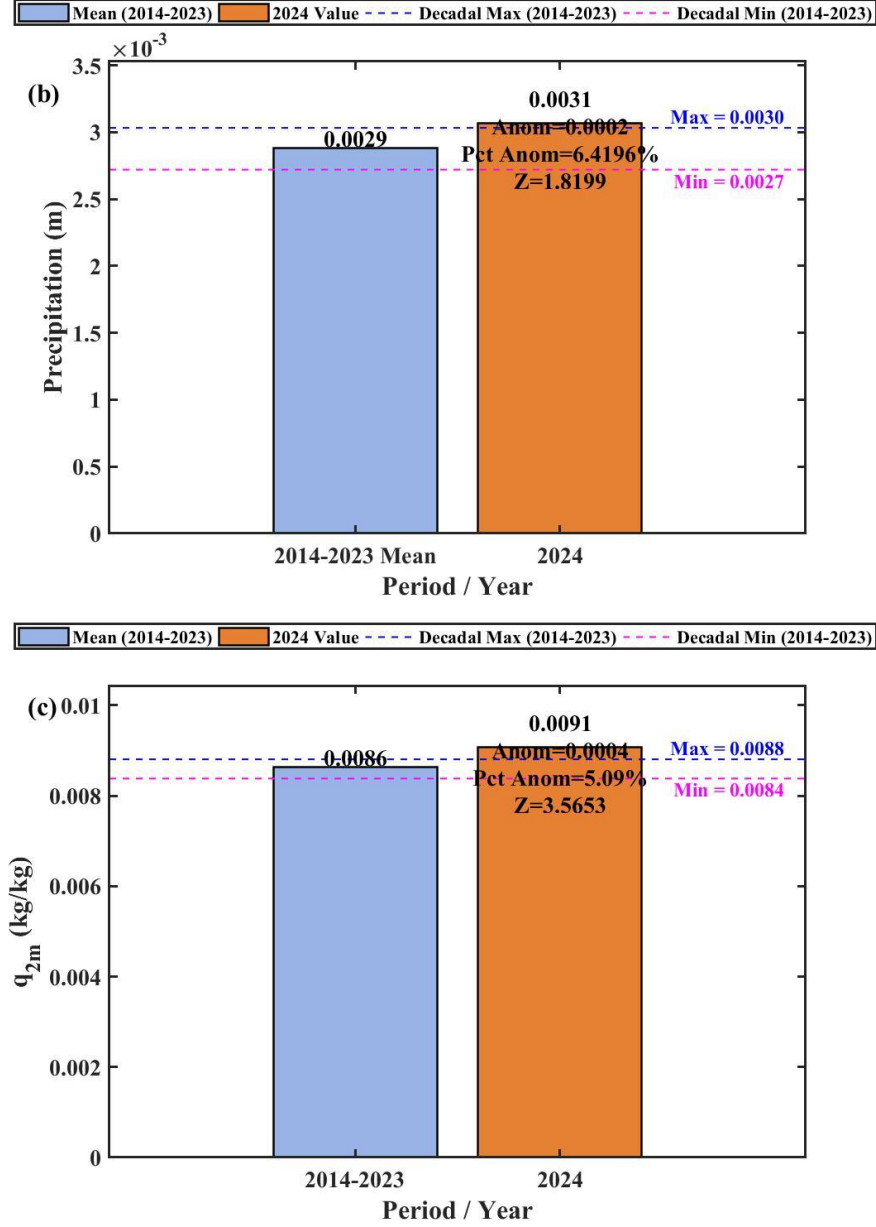


Figure R1. Comparison of the annual mean (a) total cloud cover (%), (b) precipitation (m), and (c) 2 m specific humidity (kg kg^{-1} ; q_{2m}) over China between the 2014–2023 decadal mean (blue bars) and the year 2024 (orange bars). In each subfigure, the dashed horizontal lines represent the decadal maximum (blue) and minimum (magenta) over the 2014–2023 period. Numerical values are displayed on or with the bars; for 2024, the label additionally includes the absolute anomaly (2024 minus decadal mean), the percentage anomaly relative to the decadal mean, and the standardized anomaly (Z-score, normalized by the decadal standard deviation). The legend shown at the top applies to all three panels.

2. The retrieval algorithm may need more validation. The height-dependent sensitivity threshold and clutter-removal method are reasonable, but the final cloud occurrence, layer number, CBH, CTH, and CT depend on several empirical thresholds, including

the variance criteria, the -20 dBZ filter, and the thin-layer merging/removal rules. These choices may affect thin clouds, weak high clouds, multilayer clouds, and precipitation-contaminated cases. Is it possible to include systematic validation against independent observations, such as ceilometer, radiosonde-derived cloud layers, lidar, or active satellite products?

Response: We sincerely thank the reviewer for this critical and constructive comment. We fully agree that validation against independent observations is essential to verify the reliability of our improved CVS retrieval algorithm, especially given the multiple empirical thresholds adopted in our algorithm.

To address this concern, we have conducted case-based validation using independent radiosonde observations, focusing on the challenging cloud types prone to retrieval uncertainties, including low-level thin cloud, thin mid-level cloud, thick high-level cloud, multi-layer cloud, and deep precipitating cloud. We selected six representative cases covering these categories.

For each of the six cases, we constructed standardized three-panel comparative plots and integrated them into a unified supplementary figure (Fig. S2). The left panel shows the statistical distribution of 30-minute MMCR reflectivity samples, overlaid with three height-dependent detection thresholds (S_0 , S_1 , S_2) for signal reliability validation. The middle panel presents the 30-minute time-height cross-section of MMCR radar reflectivity, with markers indicating our retrieved CBH and CTH. The right panel illustrates cloud layers diagnosed from collocated radiosonde profiles using the relative-humidity-gradient method proposed by Xu et al. (2023), with green shading denoting the identified cloud boundaries.

The detailed validation results are summarized as follows:

Case 1 (low-level thin cloud): Panels a1 and b1 show a distinct single-layer boundary-layer cloud situated at an altitude of roughly 500 m, with a vertical extent of only 200–300 m. Our variance-based ground clutter suppression effectively isolates this shallow cloud signal from low-level ground interference (b1). The CBH and CTH retrieved from MMCR match the near-surface saturated humidity layer diagnosed by collocated radiosonde profiles (c1), with nearly negligible vertical offsets between radar and radiosonde cloud boundaries. This close agreement validates the effectiveness of our variance-based criteria for distinguishing true cloud echoes from ground clutter.

Case 2 (mid-level thin cloud): This single-layer cloud continuously occupies the 4–6 km altitude range with weak-to-moderate radar reflectivity (a2, b2). The height-dependent thresholds, combined with a -20 dBZ minimum reflectivity cutoff, effectively isolate these faint mid-level cloud echoes from background noise. The excellent agreement between MMCR-retrieved cloud boundaries (CBH/CTH) and

radiosonde-derived cloud boundaries, with nearly negligible vertical offsets (c2), confirms that this cutoff reliably retains true cloud signals while excluding noise.

Case 3 (high-level thick cloud): This single-layer cloud extends from roughly 9 to 12 km with relatively weak-to-moderate reflectivity (a3, b3). After variance-based clutter suppression removes spurious low-level noise (4–6 km), the -20 dBZ reflectivity threshold is applied to isolate genuine cloud signals. The resulting MMCR-retrieved CBH and CTH align closely with the radiosonde-diagnosed saturated upper-tropospheric humidity band, with vertical offsets consistently within 0.5 km (c3), which further confirms that the -20 dBZ threshold effectively filters out noise without erroneously removing authentic cloud signals.

Case 4 (multi-layer cloud, first scenario): This case consists of vertically overlapping mid-level cloud echoes characterized by extensive moderate-to-strong radar reflectivity signals (panels a4, b4). The combination of height-dependent sensitivity thresholds and variance-based ground clutter filtering reliably isolates genuine cloud echoes from low-altitude ground interference and instrumental background noise. The time–height cross-section (b4) reveals that the cloud vertical structure evolves rapidly over the half-hour observation window, with the number of distinct cloud decks varying from one to three layers. Our algorithm accurately tracks these individual cloud layers during their formation, merging and dissipation processes, and marks the CBH and CTH of each layer with dedicated symbols, which validates the robustness of our rules for thin-cloud merging and elimination. In comparison, the radiosonde humidity profile (green shaded saturated region in c4) only provides a single instantaneous snapshot and fails to capture such temporal variability; it merely presents a unified continuous saturated layer that integrates all vertically separated cloud decks.

Case 5 (multi-layer cloud, second scenario): This analogous multi-layer case (panels a5, b5, c5) further validates the robustness of our retrieval scheme under complex multi-layer conditions. As in Case 4, our algorithm successfully resolves vertically stacked thin-to-moderate cloud layers, avoids false detection amid overlapping echoes.

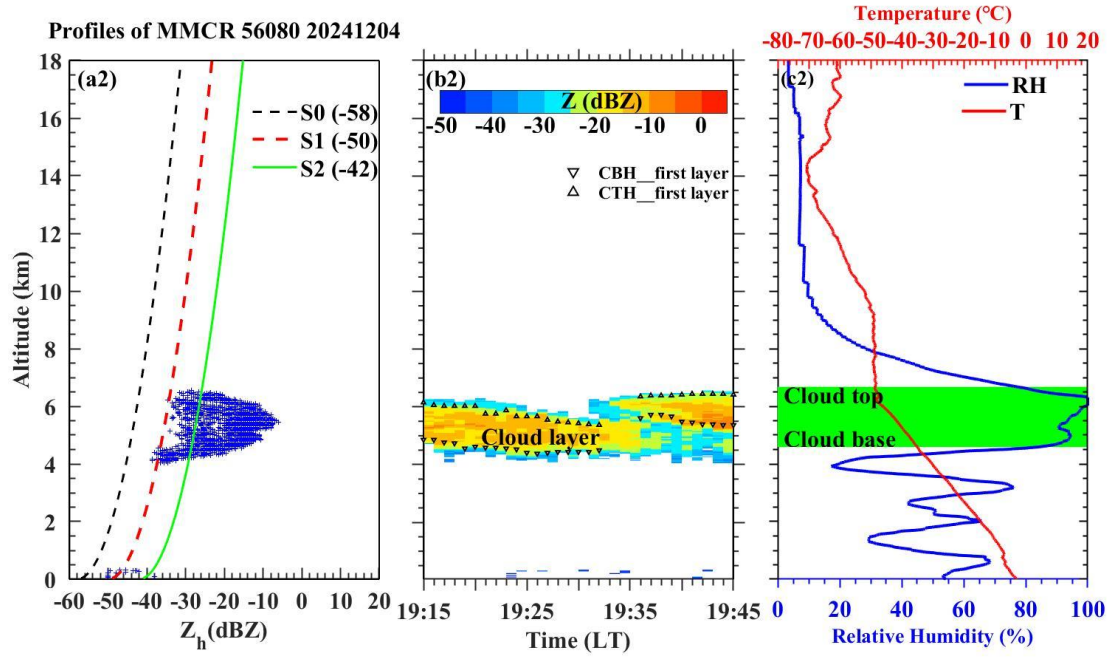
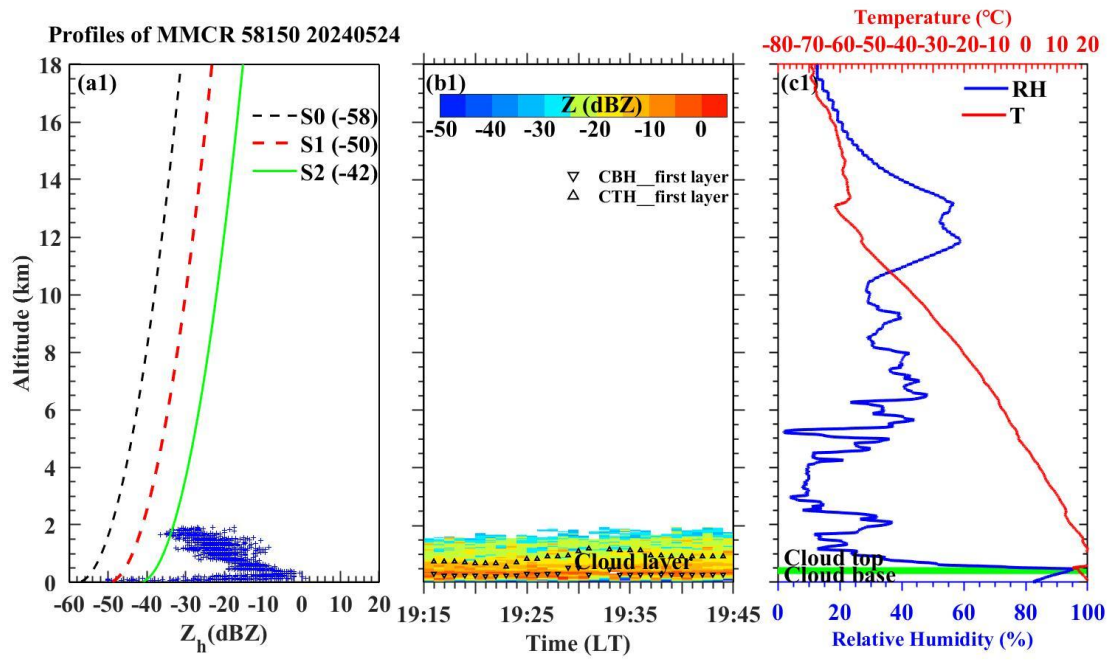
Case 6 (deep precipitating cloud): This case features a deep precipitating cloud extending from near-surface to ~11 km with strong reflectivity (a6, b6). Height-dependent thresholds and variance-based clutter filtering reliably separate cloud and precipitation signals from ground interference, and the algorithm correctly identifies the continuous cloud boundaries (CBH/CTH) throughout the observation period. The collocated radiosonde profile (c6) shows a deep saturated layer, which matches the MMCR-retrieved cloud extent closely, with only minor vertical differences (within 1 km). This confirms that the retrieval framework remains robust and produces credible cloud boundaries even for deep, heavily precipitating systems.

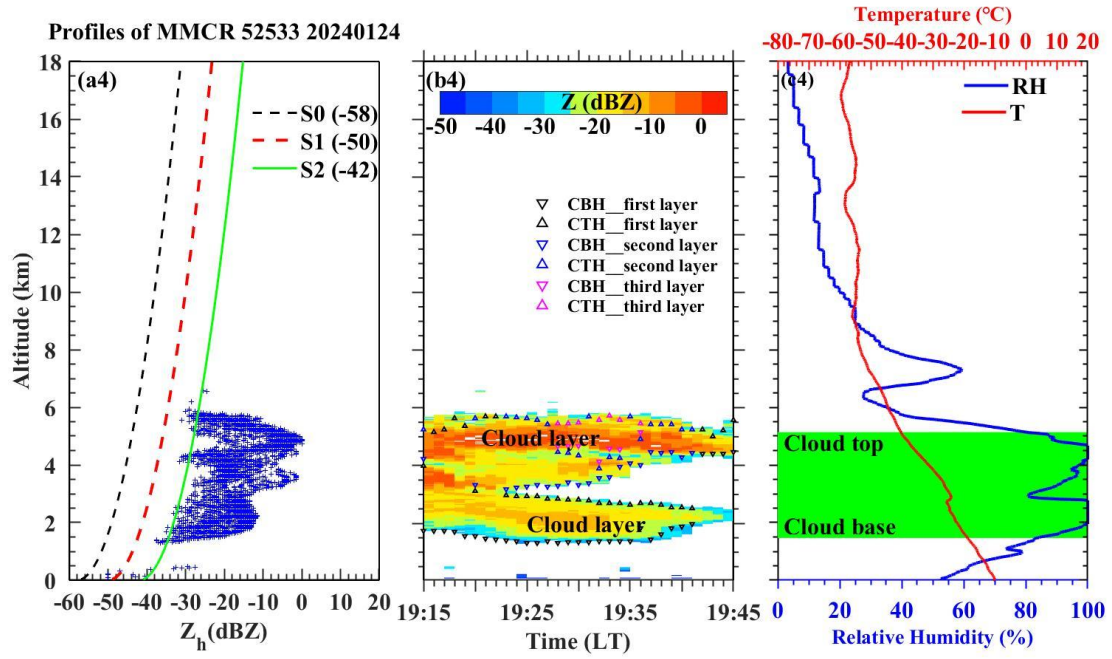
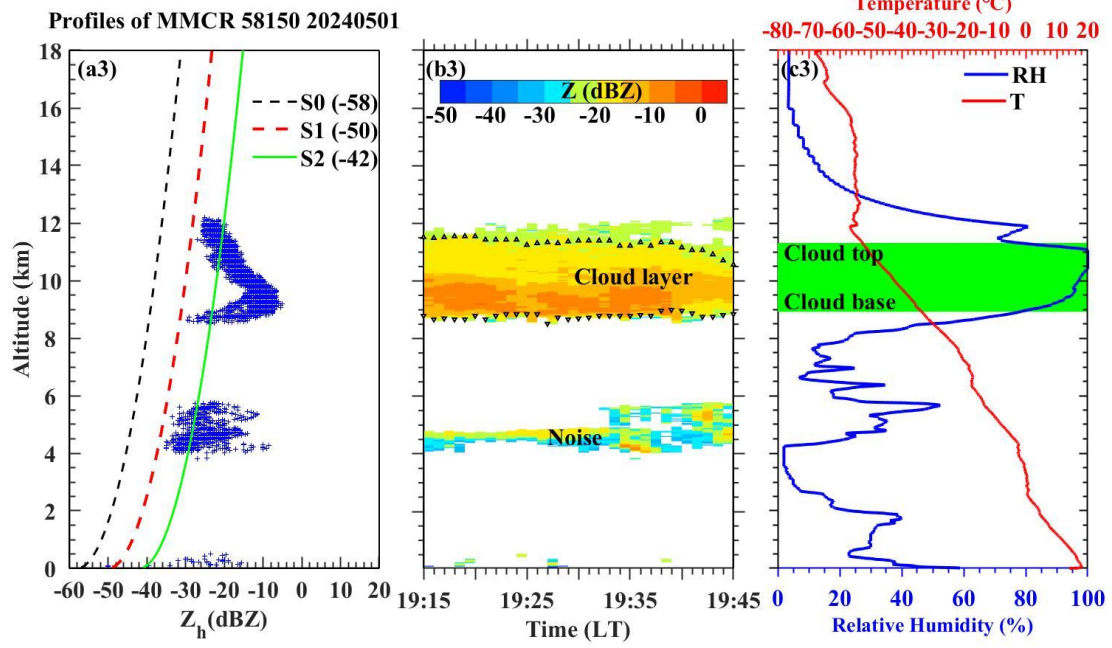
Across all six validation cases, the consistent agreement between MMCR retrievals and radiosonde-derived cloud layers demonstrates that our radar-retrieved CBH, CTH, and layer number are in good agreement with independent observations. For thin and weak clouds, the height-dependent sensitivity threshold successfully distinguishes authentic cloud echoes from instrumental noise. Minor mismatches between MMCR and radiosonde cloud retrievals are physically reasonable, primarily arising from temporal sampling mismatch: the MMCR operates at 1-min temporal resolution, whereas radiosondes are launched only twice daily.

We have added a summary of this validation exercise in Section 2.3 (CVS retrieval methods) and supplemented the new figure (Fig. S2) with a detailed descriptive caption in the supplementary materials. The revised manuscript text is presented as follows:

“To evaluate the performance of our improved retrieval algorithm for various cloud categories (including low-level thin cloud, mid-level thin cloud, high-level thick cloud, multi-layer cloud, and deep precipitating cloud), we conducted case-based validation against collocated radiosonde observations (Fig. S2). Comparisons reveal good agreement between radar-retrieved cloud boundaries and cloud limits derived from radiosonde profiles processed following the algorithm proposed by Xu et al. (2023). Vertical discrepancies of CBH and CTH are nearly negligible for thin low-level and mid-level clouds, constrained within 0.5 km for thick high-level clouds, and limited to 1 km for precipitating cloud systems.”

We hope this newly added validation analysis greatly strengthens the reliability assessment of our CVS retrieval scheme and fully resolves the reviewer’s concern. We again appreciate this insightful suggestion, which has markedly elevated the quality of this manuscript.





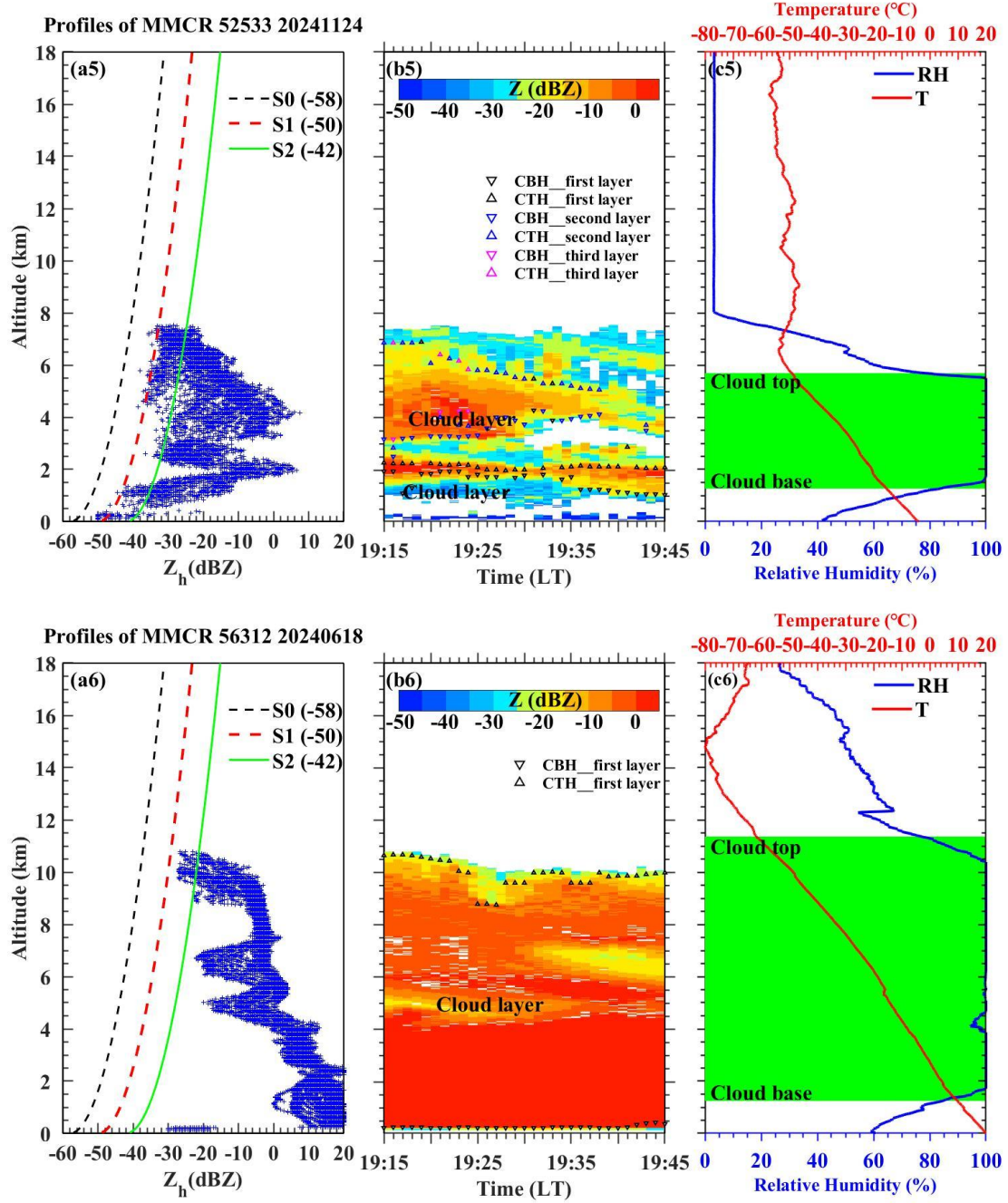


Figure S2. Comparison of six representative cases between MMCR-retrieved cloud vertical structure and collocated radiosonde cloud layers. The first column of panels shows height-dependent detection thresholds S0, S1, and S2 (with their respective threshold values indicated in brackets) overlaid with instantaneous radar reflectivity samples. The middle column presents time-height cross-sections of MMCR reflectivity factor Z (dBZ), with inverted triangles and triangles marking the retrieved cloud base height (CBH) and cloud top height (CTH), respectively. The right column displays radiosonde profiles of relative humidity (RH, blue curve) and temperature (T, red curve); green horizontal bars denote cloud boundaries diagnosed via the

humidity-gradient method of Xu et al. (2023). Each row (rows 1-6) corresponds to one validation case.

3. The spatial representativeness and scale matching should be discussed more carefully. Although the network is impressive, it is still a set of point measurements rather than an area-covering observing system. In addition, the MMCR observations are matched with ERA5 fields at 0.25° resolution, which may not represent local cloud environments well, especially over complex terrain or regions with strong surface heterogeneity. The authors may consider the sensitivity of key results to station distribution, sparse regions, complex terrain, and the point-to-grid matching method.

Response: We sincerely thank the Reviewer for this careful and constructive comment. We fully acknowledge that the 80 MMCR stations are point measurements rather than an area-covering observing system, and that matching them with 0.25° ERA5 fields may introduce scale mismatches, particularly over complex terrain and heterogeneous surfaces.

To address this concern, we have made two revisions:

(1) Sensitivity test with higher-resolution reanalysis

We repeated the key correlation analyses using ERA5-Land ($0.1^\circ \times 0.1^\circ$, ~ 9 km), which better resolves near-surface heterogeneity. The comparison, now included in the Supplementary Materials (Figs. S5), shows that the correlation signs, spatial patterns, and magnitudes for CVS metrics against near-surface thermodynamic variables are highly consistent between ERA5 and ERA5-Land. This confirms that our core results are not sensitive to the specific grid resolution or to the point-to-grid scale mismatch.

We retained ERA5 as the primary dataset because our analysis requires atmospheric profiles (atmospheric temperature at the 700 hPa level ($T_{700\text{hPa}}$) and at the 500 hPa level ($T_{500\text{hPa}}$)) to compute lower-tropospheric stability (LTS_{surf}), which ERA5-Land does not provide. Using a single, physically consistent dataset for both surface and pressure-level variables is essential. The strong agreement between the two products in the sensitivity test further demonstrates that ERA5's 0.25° resolution is adequate for capturing the large-scale thermodynamic signals relevant to CVS.

(2) Explicit discussion of the limitation in the manuscript

We have added a paragraph in Section 2.2.3 that explicitly acknowledges the scale mismatch and presents the sensitivity test as a validation, as follows:

“A spatial scale mismatch inevitably exists between the gridded ERA5 fields (~ 31 km) and the point-based MMCR observations, which may introduce uncertainties over complex terrain and regions with strong surface heterogeneity. To evaluate the sensitivity of our results to this mismatch, we repeated the key correlation analyses

using ERA5-Land ($0.1^\circ \times 0.1^\circ$, ~ 9 km), which better resolves near-surface variability. The comparison (Supplementary Figs. S5) shows that the correlation signs, spatial patterns, and magnitudes are highly consistent between the two products, confirming that our conclusions are not sensitive to the specific grid resolution. While some local-scale uncertainty is inherent in any point-to-grid comparison, the consistent spatial patterns across diverse climatic and topographic settings indicate that the identified relationships reflect robust large-scale physical mechanisms. The procedure for temporally aggregating the MMCR observations and matching them with ERA5 is described in Section 2.3.”

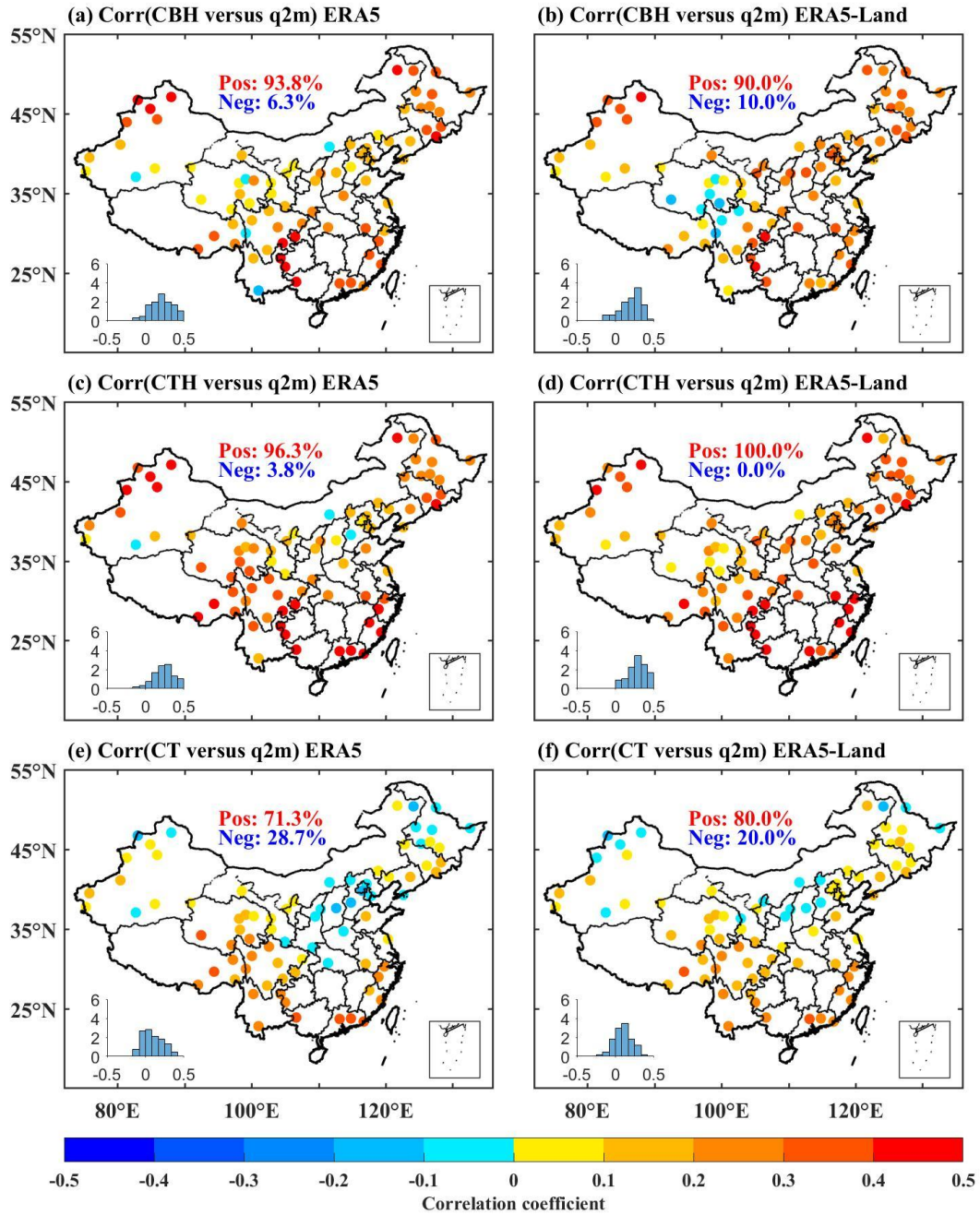


Figure S5. Comparison of the spatial correlations of CBH, CTH, and cloud thickness (CT) with 2m specific humidity (q_{2m}) from ERA5 and ERA5-land across China (2024). All atmospheric variables were spatially and temporally matched with the MMCR CBH observational data to ensure the reliability of the correlation analysis. In each panel, the probability distribution of the correlation coefficient is illustrated by a histogram, and the abbreviations “Pos” and “Neg” denote the percentages of statistically significant positive and negative correlation coefficients across the entire study domain, respectively.

4. The physical attribution is still mainly based on correlation. The reported relationships between q_{850} , LTS, WS700, and cloud properties are plausible, but the current analysis does not fully separate the effects of season, region, cloud type, and large-scale weather regime. For example, the positive relationship between q_{850} and CBH may partly reflect the co-occurrence of high humidity, deeper boundary layers, and convective regimes in summer, rather than a direct moisture effect on cloud base.

Response: We sincerely thank the reviewer for this constructive comment. We fully agree that correlations alone cannot definitively establish causality and that the effects of season, cloud type, and large-scale regime should be isolated to the extent possible. In the revised manuscript, we have taken the following steps to address this concern:

(1) Separation of seasonal and cloud-type effects

We have performed seasonal composite analyses for the correlations between all three cloud metrics (CBH, CTH, CT) and each atmospheric variable (q_{2m} , LTS_{surf} , VWS). The proportions of stations showing positive/negative correlations in each season are now reported and discussed (see Section 3.5; supplementary Figs. S6–S8). These results reveal distinct seasonal modulations. For instance, the positive CBH– q_{2m} correlation is strongest in summer (85% of stations) and weakest in spring (64.6%), supporting the interpretation that this relationship is largely governed by the seasonal prevalence of deep convective boundary layers rather than by a direct, season-independent moisture effect on cloud base. Similar seasonal contrasts are documented and discussed for LTS_{surf} and VWS, where the dominant cloud type (convective vs. stratiform) in each season is shown to condition the sign and strength of the correlations.

(2) Separation of thermodynamic and dynamic controls via joint dependence analysis

To further disentangle the intertwined effects of moisture, stability, and shear, we have introduced paired-variable joint dependence analyses (Figs. 9, 11, 13). These analyses explicitly demonstrate the conditional nature of the controls. For example, the positive effect of q_{2m} on CBH is only operative under low- LTS_{surf} (unstable)

conditions and is largely suppressed under stable stratification. This directly addresses the Reviewer’s concern by showing that the apparent positive q_{2m} –CBH correlation does not simply reflect the co-occurrence of high humidity and deep boundary layers, but rather a conditional coupling that requires convective instability.

(3) Regional information

The spatial maps of the correlations (Figs. 8, 10, 12) are retained and discussed, highlighting regional contrasts (e.g., distinct behaviour over the Tibetan Plateau, northwestern China, and the southeastern coastal regions). This preserves the geographical perspective within a nationally scaled analysis.

(4) Acknowledged limitations and future work

We acknowledge that our attribution remains correlation-based and that a formal separation by synoptic weather regimes—as the Reviewer rightly suggests—would further strengthen the mechanistic understanding. In the revised text, we have noted that while seasonal stratification captures the dominant large-scale regime shifts (e.g., monsoon vs. winter monsoon), a dedicated weather-regime analysis is beyond the scope of the current study. We have added a statement at the end of Section 4 acknowledging that while seasonal stratification captures the dominant large-scale regime shifts, a dedicated weather-regime analysis is beyond the scope of this study and is warranted in future work, as follows:

“.... Additionally, while the seasonal stratification in this study captures the dominant large-scale regime shifts (e.g., monsoon), a dedicated analysis using objective weather-typing techniques would further isolate the effects of synoptic weather regimes on CVS, which is beyond the scope of the current study.”

We believe these additions significantly strengthen the physical attribution and directly address the reviewer’s concern. The seasonal and joint-dependence analyses demonstrate that the reported relationships are not mere statistical artifacts of seasonal aggregation, but reflect genuine, regime-dependent physical couplings.

For the sake of brevity, here we only show the revised text of the CBH case, as follows,

“3.5.1 Impact of atmospheric thermodynamic factors on CBH

Figure 8 illustrates the spatial distributions of annual mean correlation coefficients between CBH and three atmospheric variables. Positive correlations between CBH and q_{2m} are found at 93.8% of all observation stations (Fig. 8a), while only 6.3% of stations show negative correlations. This widespread positive relationship indicates that climatologically moister low-level environments are generally accompanied by higher cloud bases. Notably, this relationship does not imply that increased surface moisture directly lifts the LCL. Instead, it reflects the co-variability of low-level moisture and convective instability. Seasonal composite analyses further verify that this positive relationship between CBH and q_{2m} is most pronounced in summer (85% of stations), and weakest in spring (64.6%), with winter

(74.7%) and autumn (66.3%) falling in between (Fig. S6 a-d). Such seasonal contrast demonstrates that the CBH is governed by boundary layer depth and convective regimes, instead of a straightforward moisture-driven effect on cloud base height. Under moist and unstable conditions, a more deeply developed PBL and stronger thermally driven updrafts act to elevate cloud bases, particularly for cumulus and convective cloud systems (Betts, 2004; Zhang and Klein, 2013). This relationship is statistically robust and spatially consistent across most regions, particularly over southeast China, where moist convection dominates cloud vertical development. The sparse negative correlations (6.3%) are likely governed by persistent large-scale subsidence, which decouples local moisture fluctuations from cloud formation (Wood, 2012; Myers and Norris, 2013).

In contrast, CBH exhibits predominantly negative correlations with LTS_{surf} across 97.5% of stations (Fig. 8b). The strong negative correlations are concentrated over the southeastern coastal regions of China. Higher LTS_{surf} indicates stronger lower-tropospheric stratification, which suppresses boundary-layer growth and favours shallow stratiform clouds with lower cloud bases (Klein and Hartmann, 1993; Wood and Bretherton, 2006). Conversely, reduced LTS_{surf} enhances instability, facilitating more intense turbulent mixing in the boundary layer, and promoting the development of convective clouds with higher cloud bases (Slingo, 1987). Seasonal composite analyses further verify that this negative relationship is most widespread in autumn (80.0% of stations) and summer (73.8%), and relatively less so in winter (63.3%) and spring (62.0%) (Fig. S6 e-f). This seasonality indicates that the CBH– LTS_{surf} coupling is modulated by the prevailing convective and boundary-layer regimes. The more consistent negative correlations in summer and autumn align with the dominance of deep convection and stable stratiform conditions (Zhang and Klein, 2013; Guo et al., 2016), respectively, whereas the weaker connection in spring and winter suggests that synoptic transients may at times override the local stability control (Taszarek et al., 2019). This seasonal differentiation confirms that, while LTS_{surf} exerts a primary thermodynamic control on CBH, its influence is conditioned by the seasonal evolution of boundary layer and cloud regimes (Zhang and Klein, 2013).

At the national scale, CBH exhibits a predominantly negative correlation with VWS across 77.8% of stations (Fig. 8c). This widespread negative correlation indicates that stronger vertical wind shear is generally associated with lower cloud bases. Physically, enhanced VWS promotes the entrainment of drier environmental air into the cloud layer, which intensifies droplet evaporation, reduces buoyancy, and suppresses deep convective development, lowering effective cloud bases (Weisman and Rotunno, 2000). The sparse positive correlations (22.2%) likely reflect localized regimes where moderate shear organizes convection and helps sustain updrafts, or where shear-induced low-level convergence promotes cloud formation under specific

instability conditions (Houze, 2018). Seasonal composite analyses confirm the robustness of this negative relationship, with the proportion of stations showing negative correlations ranging from 56.5% in summer to 70.0% in winter (Fig. S6 i-l). This seasonal consistency, albeit weaker than that observed for thermodynamic factors (q_{2m} and LTS_{surf}), reinforces the interpretation that VWS plays a secondary modulating role in controlling CBH, conditioned by the prevailing convective regime.

To further explore the joint constraints of atmospheric factors on CBH, we analyze the paired dependence of CBH on q_{2m} , LTS_{surf} , and VWS (Fig. 9). For the q_{2m} - LTS_{surf} combination (Fig. 9a), CBH generally increases with increasing q_{2m} , while the magnitude of this sensitivity is strongly modulated by atmospheric stability. Under low LTS_{surf} (unstable) conditions, the highest CBH values occur in moisture-abundant environments, consistent with deep boundary layers and active convective cloud development (Zhang and Klein, 2013). In contrast, under high LTS_{surf} (stable) conditions, CBH remains consistently low across nearly the entire moisture range, suggesting that strong lower-tropospheric stratification dominates the cloud base variation, confining cloud development to low-base stratiform clouds regardless of moisture availability (Klein and Hartmann, 1993; Wood and Bretherton, 2006).

The LTS_{surf} -VWS relationship (Fig. 9b) further illustrates this conditional modulation effect. In low LTS_{surf} environments, CBH tends to increase with increasing wind shear, consistent with the role of wind shear in organizing convection and modulating inflow structure under unstable conditions (Weisman and Rotunno, 2000). Under high LTS_{surf} environments, CBH remains uniformly low and shows weak sensitivity to shear, reinforcing the conclusion that stability exerts the primary constraint on cloud-base variability.

For the q_{2m} -VWS pairing (Fig. 9c), CBH increases primarily with q_{2m} , while wind shear plays a secondary modulating role. The highest CBH values occur when abundant low-level moisture coincides with weak-to-moderate wind shear, indicating that abundant low-level moisture acts as the primary driver for elevated cloud bases, while weak shear does not exert the suppressing effect typically associated with strong wind shear. This is consistent with the national-scale negative correlation between CBH and VWS shown in Fig. 8c, where strong shear environments tend to suppress cloud-base height.

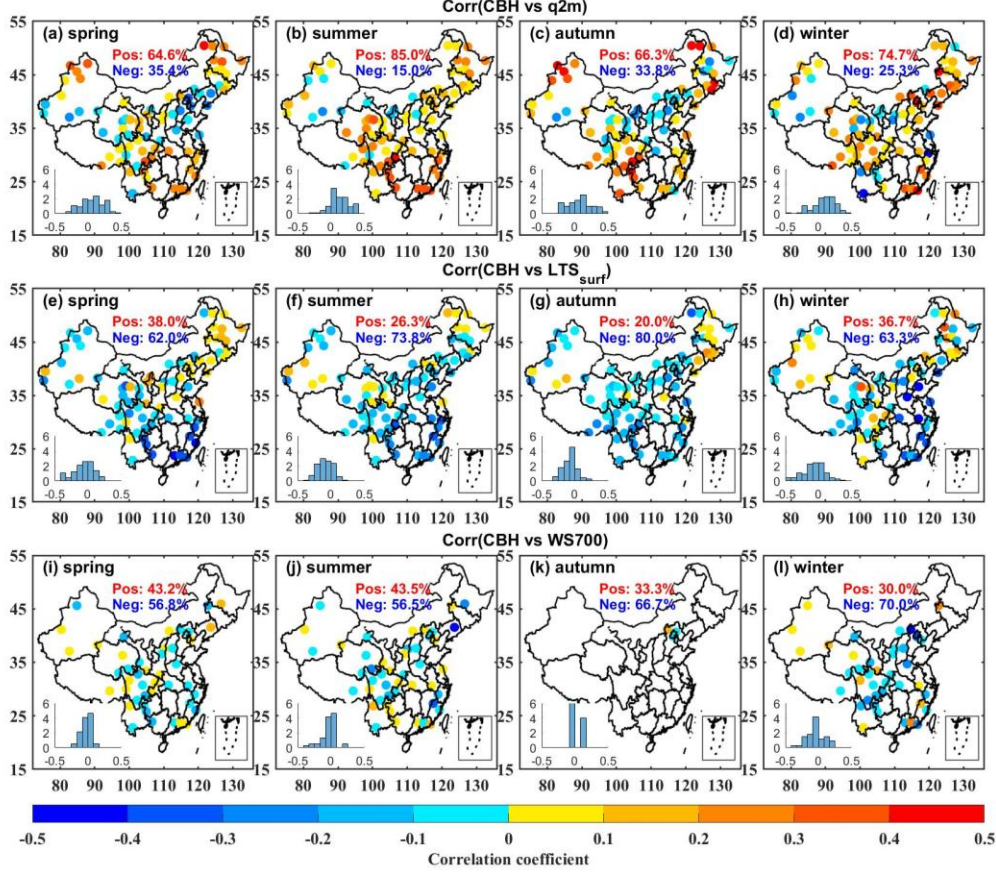


Figure S6. Seasonal mean spatial correlations of CBH with (a-d) q_{2m} , (e-h) lower-tropospheric stability (LTS_{surf}), and (i-l) vertical wind shear (VWS) across China in 2024. All atmospheric variables were spatially and temporally matched with the MMCR CBH observations. In each panel, the histogram shows the probability distribution of the correlation coefficients, and the labels “Pos” and “Neg” indicate the percentages of stations with statistically significant positive and negative correlations, respectively. ”

5.CT should be treated carefully, since it is defined as the distance between the highest cloud top and lowest cloud base and may include clear gaps in multilayer cases. Clarifying this definition would make the interpretation of CT correlations more reliable.

Response: We have explicitly clarified this definition in the revised introduction sections (Lines 125-127), as follows:

“CT represents the total cloud thickness, defined as the difference between the highest CTH and lowest CBH across all detected layers. For multi-layer cloud conditions, this definition includes the clear-sky gaps between individual cloud layers.”

6. The use of fixed pressure-level environmental variables needs caution, especially over the Plateau area. The manuscript uses q_{850} and an LTS definition based on 700 hPa and 1000 hPa, but these pressure levels may be below ground or not physically representative at high-elevation sites.

Response: We thank the reviewer for this critical comment. We fully agree that adopting fixed pressure-level variables (i.e., 850hPa specific humidity (q_{850}) and the traditional lower tropospheric stability ($LTS = \theta_{700hPa} - \theta_{1000hPa}$)) is inappropriate over the Tibetan Plateau. In the revised manuscript, we have replaced these with elevation-dependent formulations that maintain physical representativeness across all terrain heights. The specific modifications are as follows:

Low-level moisture:

The q_{850} has been replaced with 2 m specific humidity (q_{2m}), which is calculated from the ERA5 2 m dewpoint temperature ($T_{d,2m}$) and surface pressure (p_{surf}) using standard psychrometric formulas. Because q_{2m} is defined at 2m above the surface, it inherently follows the topography, making it a physically consistent measure of low-level moisture across all terrain heights, including the Tibetan Plateau.

Lower-tropospheric stability and vertical wind shear:

For both LTS and VWS, we adopt a unified terrain-following criterion based on surface elevation rather than using a single fixed pressure level:

For stations with surface elevation < 3 km (covering most of eastern and central China), we use the 700 hPa level to calculate LTS ($\theta_{700hPa} - \theta_{surf}$) and WS700. This is consistent with classical definitions for lowland regions.

For stations with surface elevation ≥ 3 km (typical of the Tibetan Plateau), we raise the reference pressure level to 500 hPa to calculate LTS ($\theta_{500hPa} - \theta_{surf}$) and WS500.

This elevation-dependent approach ensures that the vertical distance between the surface and the reference pressure level is roughly comparable ($\sim 2\text{--}3$ km) across all stations (lowlands: surface $\rightarrow$ 700 hPa; Plateau: surface $\rightarrow$ 500 hPa). This prevents the 700 hPa level—which lies within the highly variable and friction-influenced near-surface layer over the Plateau—from artificially dominating the stability and shear calculations, thereby providing a more robust and physically consistent quantification of the large-scale thermodynamic and dynamical controls on cloud vertical structure.

Reanalysis and robustness verification:

All correlation and joint-dependence analyses presented in Sections 3.5 have been repeated using the updated variables. The revised results, including the spatial distributions, correlation signs, and statistical significance for the relationships

between CBH, CTH, CT and moisture, stability as well as wind shear are shown in Figures 8-13. We have added detailed descriptions of the above modifications in Section 2.2.3 (ERA5 reanalysis) and included a brief clarification in Section 3.5.

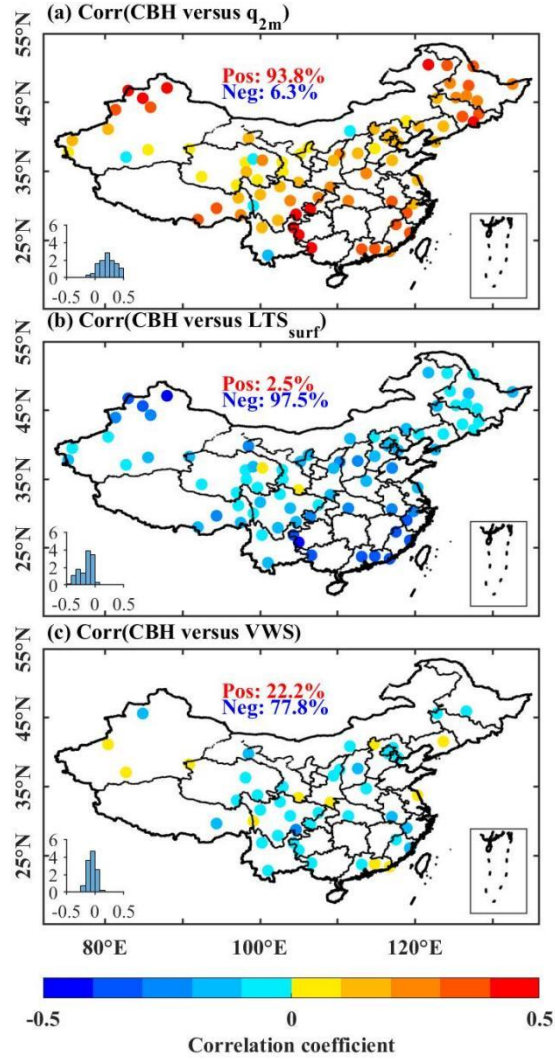


Figure 8. Spatial distributions of correlation coefficients of CBH with lower-tropospheric stability (LTS), 2 m specific humidity (q_{2m}), and vertical wind shear (VWS) across China (2024). Here, LTS_{surf} is defined as the difference between potential temperature at the reference pressure level (700 hPa for low-elevation sites and 500 hPa for high-elevation sites) and surface potential temperature. The VWS is calculated at the same reference levels following the elevation-dependent scheme described in Section 2.2.3. All atmospheric variables were spatially and temporally matched with the MMCR CBH observational data to ensure the reliability of the correlation analysis. In each panel, the probability distribution of the correlation coefficient is illustrated by a histogram, and the abbreviations “Pos” and “Neg” denote the percentages of statistically significant positive and negative correlation coefficients across the entire study domain, respectively.

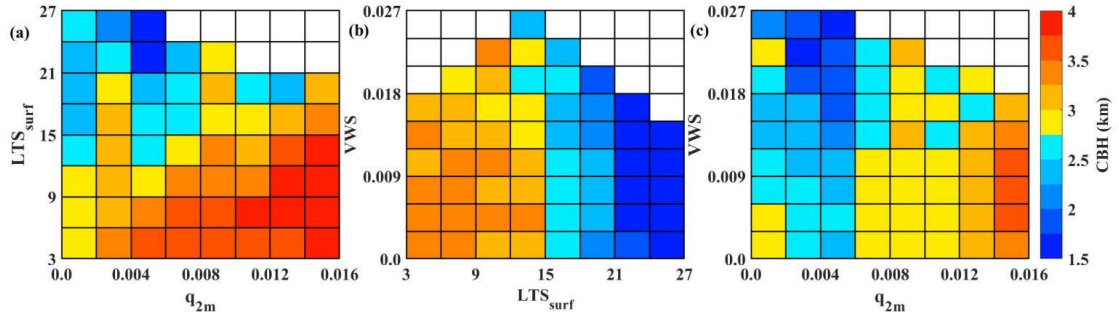


Figure 9. Bivariate regulation of CBH by thermodynamic and dynamical factors across China in 2024, based on observations from 80 MMCR stations. Each panel illustrates the response of CBH to the combined modulating effects of a specific pair of key atmospheric factors: (a) q_{2m} and LTS_{surf} , (b) LTS_{surf} and VWS , and (c) q_{2m} and VWS . All ERA5 reanalysis variables were spatially and temporally collocated with MMCR observations to ensure the validity and reliability of this bivariate joint dependence analysis.

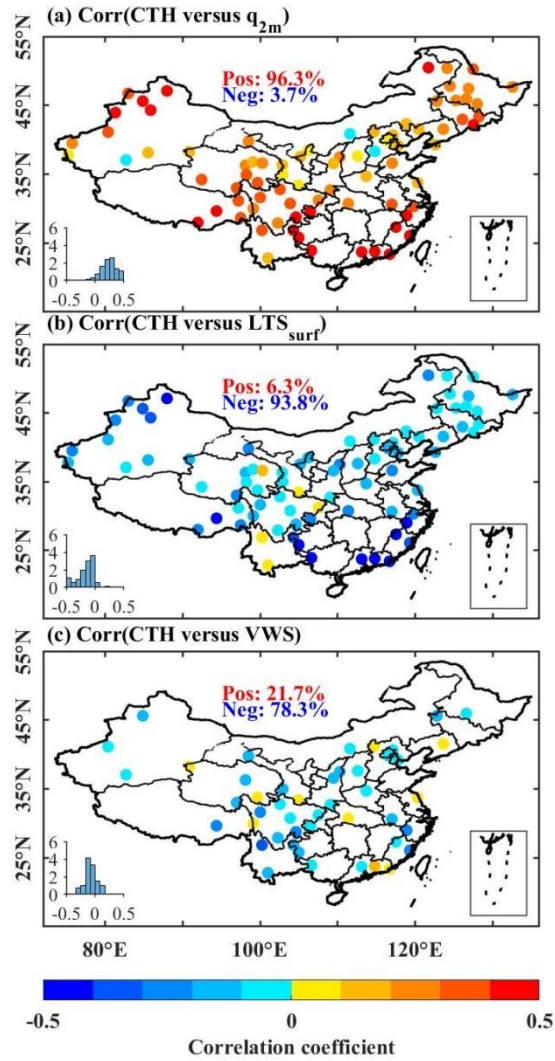


Figure 10. Similar as Figure 8, but for the CTH.

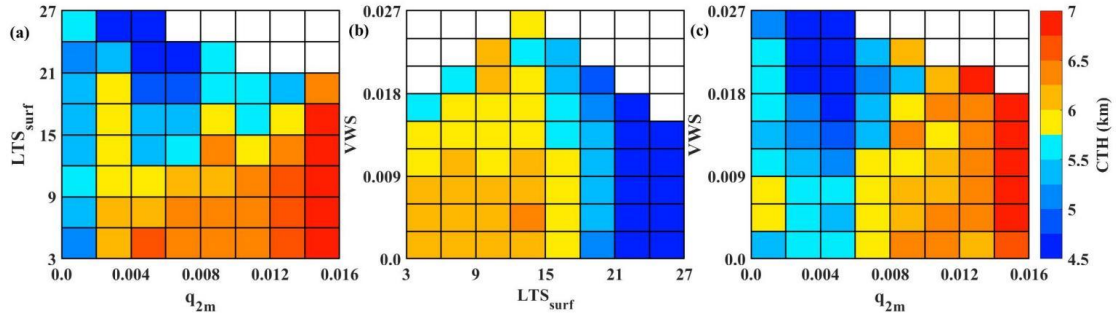


Figure 11. Similar as Figure 9, but for CTH.

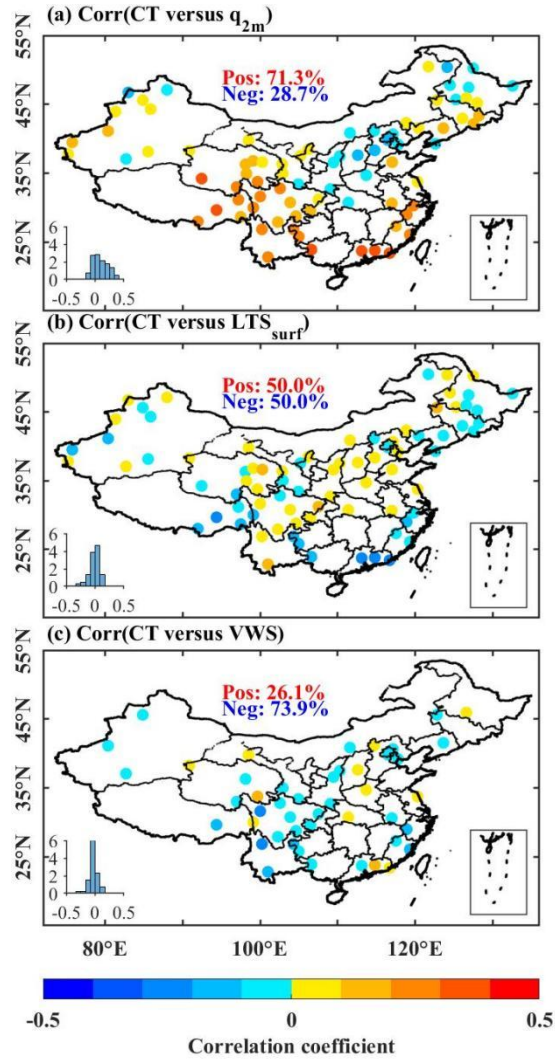


Figure 10. Similar as Figure 8, but for CT.

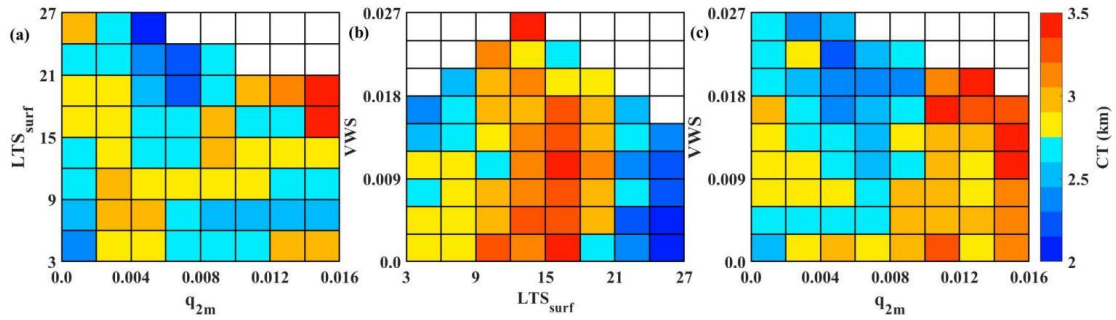


Figure 13. Similar as Figure 9, but for CT.

The sentences “*In this study, we use ERA5 data for 2024 to examine the impacts of LTS and specific humidity on CVS. For this purpose, hourly temperature at 1000 hPa and 700 hPa, and specific humidity at 850 hPa (q_{850}) are extracted for all 80 selected MMCR stations.*” in the section 2.2.3 was revised as follow:

“In this study, we use ERA5 data for 2024 to examine the impacts of LTS and specific humidity on CVS. For this purpose, hourly 2 m air temperature (T_{2m}), atmospheric temperature at the 700 hPa level (T_{700hPa}) and at the 500 hPa level (T_{500hPa}), 2 m dewpoint temperature ($T_{d,2m}$), and surface pressure (p_{sfc}) are extracted for all 80 selected MMCR stations. The 2 m specific humidity (q_{2m}) is calculated from $T_{d,2m}$ and p_{surf} using standard psychrometric formulas. Because q_{2m} is defined at 2 m above the surface, it inherently follows the topography, making it a physically consistent measure of low-level moisture across all terrain heights, including the Tibetan Plateau.”

The updated metrics also improve the reliability of analyses regarding thermodynamic controls on cloud vertical structure across diverse terrains, especially over the Tibetan Plateau.

Reviewer #3:

'Comment on egusphere-2026-1091'.

General Comments

The manuscript led by Hui Xu and Jianping Guo presents a national-scale characterization of cloud vertical structure across China using a ground-based millimeter cloud radar network. The topic is important, and the dataset has potential value for understanding regional cloud climatology. The authors state that, to their knowledge, this is the first national-scale, high-frequency characterization of cloud vertical structure across China using a coordinated ground-based radar network, and that the study systematically quantifies thermodynamic, dynamical, and land-surface controls.

I have several major concerns and questions that need to be addressed before publication. In particular, the manuscript would benefit from a more explicit discussion of how these radar-derived statistics could be used (e.g., the connection between the observational findings and their implications for model evaluation or improvement, especially from only one year of data). I also think the authors need to be cautious about the interpretation of single-layer clouds and land-surface coupling.

Response: We thank the reviewer for his/her comprehensive evaluation and thoughtful comments, which help tremendously to improve the quality of our work. We have tried our best to address the reviewer's concerns one by one.

Per your kind suggestions, substantial changes have been made, including: (1) adding a more explicit discussion on how the one-year radar-derived statistics can be used for model evaluation and improvement, and acknowledging the caveats of using only one year of data, (3) revising the interpretation of land-cover influences on cloud base height (CBH) to avoid overstating causality, particularly for single-layer clouds-clarifying throughout the manuscript that the observed land-cover contrasts represent statistical associations rather than pure surface-driven control.

For clarity purpose, here we have listed the reviewer's comments in **black**, followed by our responses in **blue**, and the modifications to the manuscript are in *italics*. We sincerely hope that the reply and the revisions can satisfy the reviewer's expectations.

Major comments:

1. I recommend adding a more explicit discussion of how these radar-derived statistics could be used. Please clarify how the findings in this study can help improve weather and climate predictions. At present, the manuscript describes the

observational characteristics well, but the pathway from these findings to improved model prediction is not sufficiently clear.

Response: We thank the reviewer for this constructive suggestion. To address this gap, we have supplemented targeted elaborations in the Conclusions (Section 4) to clearly illustrate the complete pathway from our CVS statistics toward model optimization and enhanced prediction skill, as follows:

“Overall, this study provides a high-resolution, observationally constrained snapshot of cloud vertical structure across China and establishes a quantitative framework linking CVS metrics to thermodynamic, dynamical, and land-surface controls (Figure 15). *These statistically derived linkages can directly inform model improvement in two ways. First, the observed sensitivities of CBH and CTH to LTS_{surf} and q_{2m} offer quantitative benchmarks for calibrating boundary-layer and convective parameterizations—the dominant sources of cloud-related uncertainty in weather and climate models (Bony et al., 2015; Cesana and Waliser, 2016). Second, the land-cover contrasts in CBH provide constraints for evaluating surface–atmosphere coupling in land surface models. Although this one-year record does not support long-term trend analysis, it establishes a robust baseline against which model-simulated CVS can be evaluated across timescales, especially when combined with multi-year satellite or reanalysis products, thereby supporting iterative improvement of cloud schemes and enhancing prediction skill from weather to climate scales....*”

2. The use of only one year of data needs more justification. The results appear to be based primarily on one year of observations, 2024. The authors should clearly state this limitation and explain how representative 2024 is relative to longer-term climatology. One year of data can provide valuable high-frequency observational statistics, but it may not be sufficient to draw robust climatological conclusions or to claim direct implications for model improvement. The authors should consider discussing whether 2024 was meteorologically typical or anomalous, and whether interannual variability could affect the reported cloud vertical structure statistics.

Response: We sincerely thank the reviewer for raising this insightful and critical comment regarding the representativeness of our single-year dataset. We fully agree that a single year of observations cannot constitute long-term climatology, and we have addressed this concern from three perspectives: (i) justification for selecting 2024, (ii) a quantitative representativeness assessment using ERA5 reanalysis, and (iii) tempered language throughout the revised manuscript.

(1) Why 2024 was selected

Prior to 2024, fewer than 30 MMCRs were operational across China, which was insufficient for reliable national-scale analysis of cloud vertical structure (CVS). In 2024, the network underwent a major expansion to nearly 120 stations, of which 80 met our strict data-quality criterion (≥ 100 valid observation days per year, defined as calendar days with at least 8 hours of valid MMCR measurements). Thus, 2024 represents the first year in which a sufficiently dense observing network became available, making it the only feasible foundation for this pioneering investigation. This justification has been added to Section 2.1.1 of the revised manuscript, as follows:

“MMCR data have been widely used in cloud boundary detection (e.g., Zhang et al., 2017; Zhou et al., 2019; Fang et al., 2023) and exhibit strong consistency with radiosonde observations (Wang et al., 2016; Zhao et al., 2017; Chen et al., 2022). In this study, MMCR data for the year of 2024 were obtained from the China Meteorological Administration (CMA). Of the 120 MMCR stations operating across China in 2024, only those with at least 100 valid observation days annually (*defined as calendar days with at least 8 hours of valid MMCR measurements*) were retained to ensure data quality. This criterion resulted in the selection of 80 stations for subsequent analysis (Fig. 1). *Notably, we selected 2024 because it was the first year in which the MMCR network achieved sufficient density for national-scale analysis. Before 2024, fewer than 30 stations were operational nationwide, which was inadequate for a robust spatial characterization of CVS. The major expansion in 2024, with nearly 120 MMCRs deployed, made this pioneering investigation feasible. Even though this single-year dataset does not constitute a long-term climatology, it provides the first observationally dense and vertically resolved national snapshot of CVS across China.*”

(2) Representativeness of 2024 relative to the past decade

Following the reviewer's suggestion, we evaluated the representativeness evaluation of 2024 using ERA5 reanalysis data for 2014 to 2023 as the climatological baseline. We calculated standardized anomalies (Z-scores) of annual mean total cloud cover, precipitation, and 2m specific humidity (q_{2m}) in 2024. A Z-score within ± 2 is generally considered to reflect typical interannual variability. The key results are summarized in Figure R1 (provided below for the reviewer's reference only), as follows,

Total cloud cover: The ERA5-derived annual mean cloud cover for 2024 is 54.54%, nearly identical to the 2014–2023 climatological mean of 54.05% (relative deviation 0.9%, Z-score well below 1.0). This indicates that the overall cloud amount in 2024 falls well within the range of natural interannual variability, and that our MMCR-derived cloud occurrence statistics are not unduly influenced by anomalous

cloud cover. This supports the reliability of the CVS metrics (CBH, CTH, CT) derived from the 2024 observations.

Precipitation: The Z-score for annual mean precipitation in 2024 is 1.8, indicating a notably wetter-than-normal year.

Low-level moisture: 2024 shows a pronounced positive anomaly in q_{2m} , with a Z-score of 3.5, representing an exceptionally high value relative to the past decade.

Rather than undermining our conclusions, these anomalous moisture and precipitation conditions provide a valuable “natural experiment” that reinforces the physical mechanisms proposed in our study. As we demonstrate in Section 3.5, enhanced low-level moisture promotes deeper vertical cloud development. The anomalously high precipitation in 2024 is consistent with this enhanced moisture-driven convection, and it aligns with our observed elevated cloud top heights and cloud thickness under humid conditions. In other words, 2024 exhibited near-normal cloud frequency but extreme low-level moisture—exactly the combination that our core argument predicts: moisture availability primarily controls the vertical extent of clouds once they form, rather than their occurrence frequency. Therefore, the CVS–thermodynamic relationships we derive are not artifacts of an anomalous year; rather, they are physically consistent and likely conservative relative to drier years.

We acknowledge that the single-year nature of the dataset precludes definitive multi-year climatological conclusions. We have therefore adopted a cautious tone throughout the manuscript, replacing absolute statements with precise wording such as “first observational assessment for 2024” and “an unprecedented snapshot.” In the Abstract and Conclusions, we explicitly state that this record provides a baseline for future multi-year evaluations rather than long-term climatology.

(3) Specific textual revisions

We have revised the Abstract as follows:

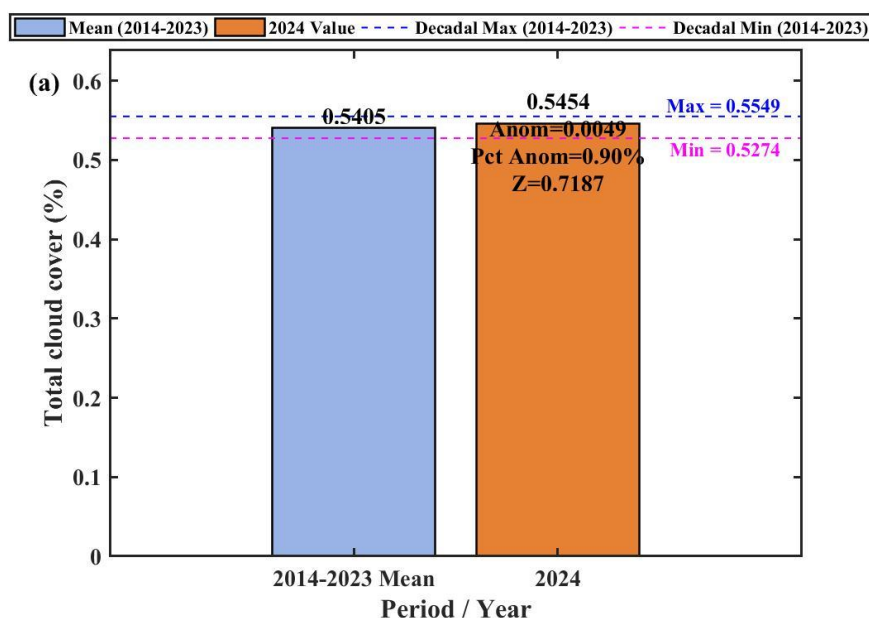
“Using a newly established national network of 80 Ka-band millimeter-wave cloud radars (MMCRs), *here we present a high-spatiotemporal-resolution (vertical resolution of 30 m, temporal resolution of 1 min) characterization of CVS across China based on one year (2024) of observations*, and quantify its thermodynamic, dynamical, and land-surface controls. ”

In the Summary and Conclusions, we now state:

“This study presents the first national-scale, high-spatiotemporal-resolution *analysis of CVS across China based on observations from a coordinated network of 80 Ka-band cloud radars during 2024, providing an unprecedentedly detailed snapshot (30 m vertical, 1 min temporal resolution) of cloud vertical structures and their governing factors.*”

“Overall, this study provides a high-resolution, observationally constrained snapshot of cloud vertical structure across China and establishes a quantitative framework linking CVS metrics to thermodynamic, dynamical, and land-surface controls (Figure 15). ... *Although this one-year record does not support long-term trend analysis, it establishes a robust baseline against which model-simulated CVS can be evaluated across timescales, especially when combined with multi-year satellite or reanalysis products, thereby supporting iterative improvement of cloud schemes and enhancing prediction skill from weather to climate scales. Future work should extend this analysis to multi-year datasets to assess interannual variability and explore the role of CVS in extreme weather events and regional climate feedbacks....*”

We believe these revisions and the accompanying analysis adequately address the Reviewer’s concern. We are grateful for the suggestion, which has significantly strengthened the manuscript.



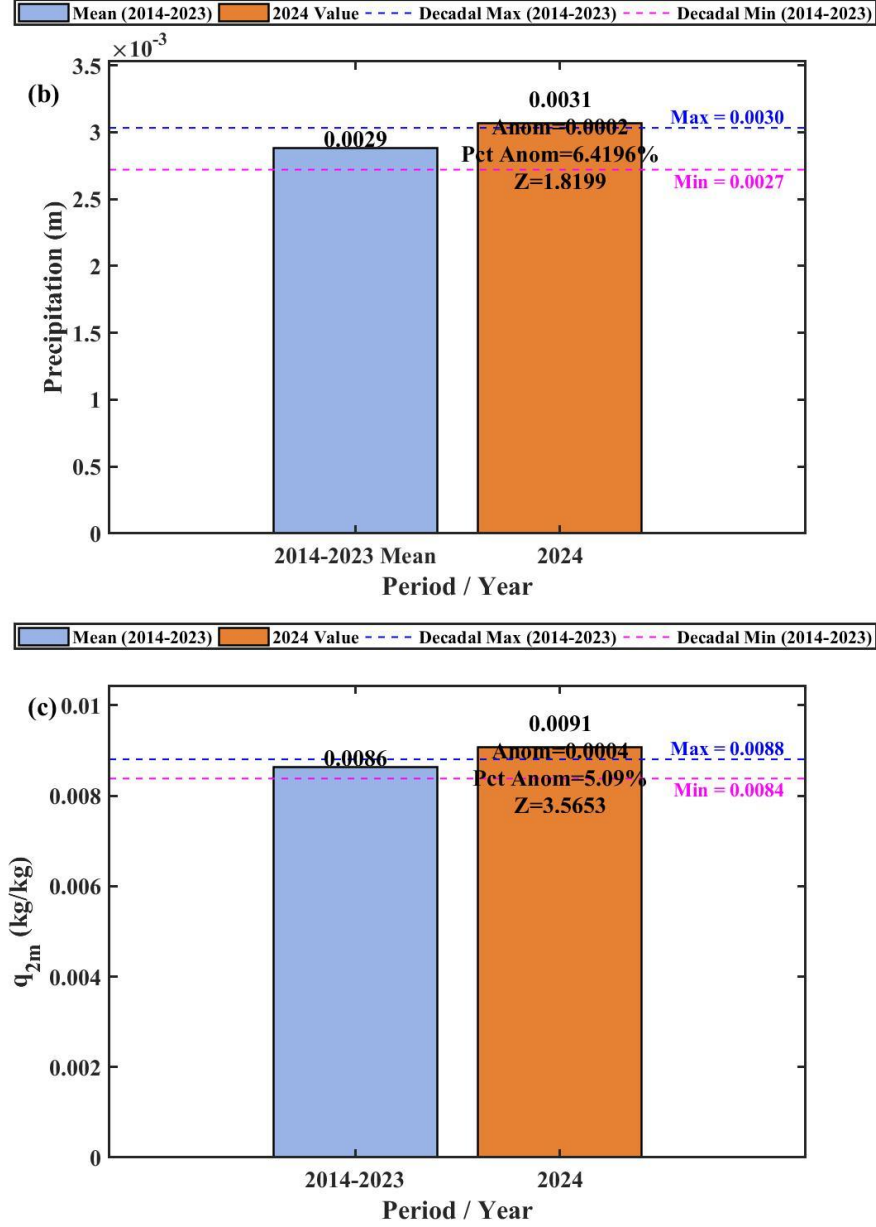


Figure R1. Comparison of the annual mean (a) total cloud cover (%), (b) precipitation (m), and (c) 2-m specific humidity (kg kg^{-1} ; q_{2m}) over China between the 2014–2023 decadal mean (blue bars) and the year 2024 (orange bars). In each subfigure, the dashed horizontal lines represent the decadal maximum (blue) and minimum (magenta) over the 2014–2023 period. Numerical values are displayed on or with the bars; for 2024, the label additionally includes the absolute anomaly (2024 minus decadal mean), the percentage anomaly relative to the decadal mean, and the standardized anomaly (Z-score, normalized by the decadal standard deviation). The legend shown at the top applies to all three panels.

3. Interpretation of single-layer clouds and land-surface coupling. Please clarify whether the single-layer cloud category includes high-level clouds. If so, the discussion in Section 3.7 may need to be reconsidered. High-level single-layer clouds

are not necessarily strongly coupled to land-surface processes, whereas low-level clouds are more directly influenced by boundary-layer thermodynamics and land-atmosphere interactions. One suggestion could be: separating single-layer clouds by cloud-base or cloud-top height before discussing land-surface controls. Otherwise, the relationship between single-layer cloud occurrence and land-surface properties may be difficult to interpret physically.

Response: We sincerely thank the reviewer for this insightful comment, which has substantially improved the physical interpretation of land–atmosphere coupling in our study. Following the reviewer’s suggestion, we have reanalyzed the land surface modulation of cloud vertical structure by focusing on low clouds ($CTH < 3$ km) and separating them into all-hour low clouds and afternoon (1400–1800 LT) single-layer low clouds. Key results based on median CBH are summarized below:

Diurnal uplift: Afternoon median CBH is systematically higher (e.g., barren: $1.32 \rightarrow 1.44$ km; grasslands: $0.99 \rightarrow 1.26$ km; cropland/natural vegetation mosaics: $0.48 \rightarrow 0.57$ km), consistent with daytime boundary-layer deepening.

Amplified land-cover contrasts: The diurnal increase is most pronounced over moist, vegetated surfaces (e.g., evergreen broadleaf +41.7%, croplands +33.3%) and smallest over dry surfaces (barren +9.1%) or water (+3.9%), reflecting the balance between sensible heating and evapotranspiration.

The systematically higher afternoon CBH is jointly driven by the restriction to single-layer clouds and the afternoon deepening of the boundary layer, while land-cover heterogeneity further modulates local cloud-base height through differential surface fluxes.

The 3.6 Land surface modulation of cloud vertical structure Section is revised as follows,

“3.6 Land surface modulation of cloud vertical structure

Beyond atmospheric thermal and dynamical factors, land-surface characteristics also influence cloud vertical structure through their effects on PBL moisture, surface energy partitioning, and turbulence (e.g., Bonan, 2008; Fu et al., 2020; Wang et al., 2021). Since CBH is tightly coupled to PBL thermodynamics, it serves as a useful metric for assessing surface – cloud coupling. This coupling is only meaningful for boundary-layer clouds; high-level single-layer clouds are dominated by large-scale upper-tropospheric processes and, as confirmed in our analysis, are insensitive to surface type. We therefore focus on single-layer low clouds ($CTH < 3$ km), which are largely confined within the boundary layer. To quantify the land-surface influence, we compare CBH across land-cover types for (i) all-hour low clouds and (ii) afternoon (1400 – 1800 LT) single-layer low clouds (Fig. 14). The afternoon subset captures the period of strongest coupling, when the boundary layer is fully developed and

land-atmosphere fluxes are maximized. .

3.6.1 All-hour low clouds

Under all-hour conditions, low clouds ($CTH < 3$ km) exhibit a systematic dependence of CBH on underlying land cover type (Fig. 14, left panels). Barren land (type 10) shows the highest median CBH (1.32 km), consistent with limited surface moisture availability and elevated LCLs. Densely vegetated surfaces yield markedly lower medians: cropland/natural vegetation mosaics (type 9) record the lowest value (0.48 km), followed by evergreen broadleaf forests (type 2, 0.72 km), deciduous broadleaf forests (type 3, 0.72 km), and croplands (type 7, 0.72 km). Water bodies (type 1, 1.02 km) and urban and built-up lands (type 8, 0.90 km) fall in the intermediate range.

These contrasts can be explained by the biophysical properties of the land cover. Forests sustain high evapotranspiration, which moistens the boundary layer and lowers the lifting condensation level, favouring lower cloud bases (Spracklen et al., 2012; Zhang et al., 2024). In addition, the greater surface roughness and lower albedo of forests enhance turbulent exchange and boundary-layer growth, promoting cloud formation, although the net effect of deeper mixing may partially offset the moisture-driven lowering. Overall, the moisture supply over vegetated surfaces appears to dominate, yielding lower CBH relative to barren land. This interpretation aligns with studies showing that land-use and land-cover change can modify CBH by altering surface energy partitioning and boundary-layer thermodynamics (Syktus and McAlpine, 2016; Xu et al., 2022; Duveiller et al., 2023).

3.6.2 Afternoon single-layer low clouds

Land cover type exerts a stronger modulating effect on the CBH of afternoon single-layer low clouds (Fig. 14, right panels). The overall ranking of median CBH is consistent with the all-hour pattern: barren land remains highest (1.44 km), while cropland/natural vegetation mosaics remain lowest (0.57 km). Notably, afternoon CBH is systematically higher than the all-hour climatology across all land-cover types, with a mean increase of approximately 21.7%. The diurnal increase is most pronounced over densely vegetated surfaces—evergreen broadleaf forests (+41.7%), croplands (+33.3%), and woody savannas (+32.1%)—and smallest over barren land (+9.1%) and water bodies (+3.9%).

The systematically higher afternoon CBH primarily reflects the deepening of the boundary layer and the associated rise in the LCL due to strong surface heating. Additionally, restricting the sample to single-layer clouds may exclude very low cloud bases typical of multi-layer or decoupled stratiform decks, further contributing to the elevated median values. The amplified land-cover contrasts during afternoon indicate that boundary-layer evolution under strong insolation is highly sensitive to surface

heterogeneity. Heterogeneous landscapes can generate mesoscale circulations and spatial gradients in moisture and heat fluxes that modulate cloud initiation and CBH (Rieck et al., 2014).

The small increase over barren land is expected, as its cloud base is already elevated under all-hour conditions due to persistent moisture limitation. The modest rise over cropland/natural vegetation mosaics (+18.8%)—despite having the lowest absolute CBH—is consistent with strong evapotranspiration partially counteracting the boundary-layer deepening. Water bodies show minimal diurnal change (+4.4%), reflecting the large thermal inertia that suppresses the amplitude of boundary-layer development.

Overall, Fig. 14 demonstrates a measurable influence on CBH, with the strongest contrasts emerging for afternoon single-layer low clouds. These results highlight the importance of surface-driven moisture supply, energy partitioning, and boundary-layer dynamics in shaping cloud-base variability. Similar forest–open land contrasts in CBH have been reported in other regions (e.g., tropical montane environments; Trivedi et al., 2025), suggesting that land-surface modulation of low cloud vertical structure is a robust feature across diverse geographic settings.

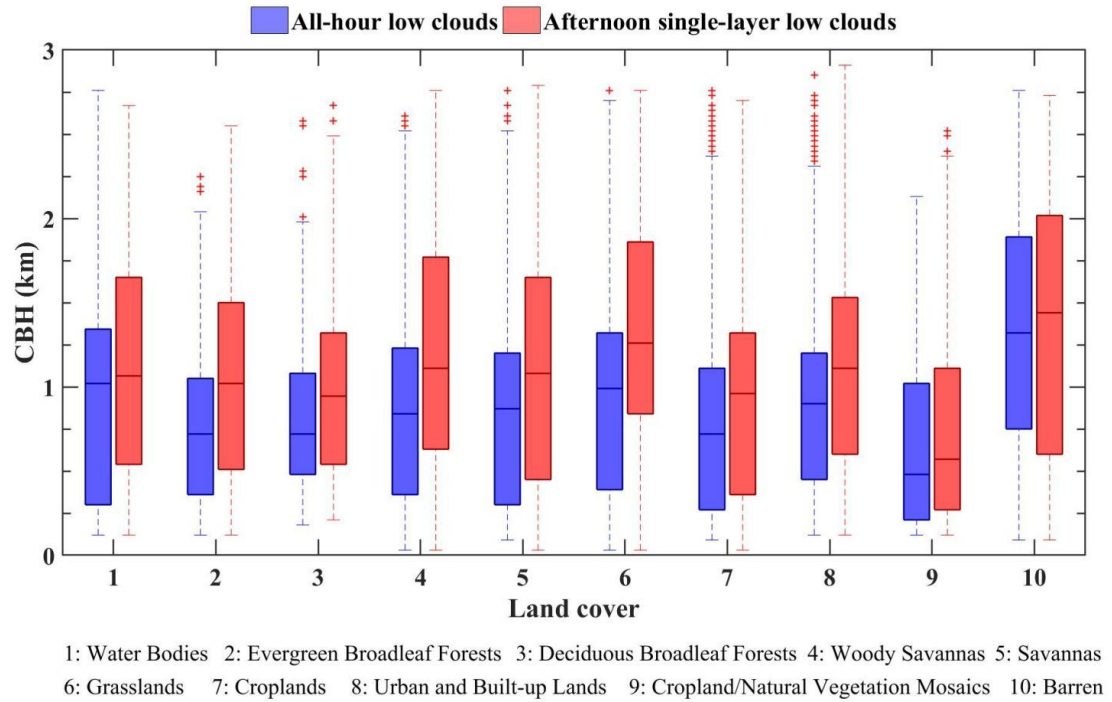


Figure 14. Land-surface influence on CBH across China in 2024, based on 80 MMCR stations. Blue bars indicate all hour low clouds, and red bars represent afternoon single-layer low clouds. Land cover types are derived from the MODIS Land Cover Type Yearly Climate Modeling Grid product (MCD12C1;

<https://ltdsweb.modaps.eosdis.nasa.gov/missions-and-measurements/products/MCD12C1>).

4. Please explain the scientific motivation for separating two-layer clouds from multi-layer clouds.

Response: We thank the reviewer for this question. In Figure 3, we deliberately separate two-layer clouds from multi-layer clouds (defined as three or more cloud layers) because they exhibit distinct spatial characteristics and are governed by different formation mechanisms.

From an observational perspective, our prior near-global radiosonde study (Xu et al., 2023) demonstrated that two-layer configurations account for 62.2% of all broadly defined multi-layer cloud occurrences (clouds with ≥ 2 layers), and importantly, show no consistent regional preference. This characteristic spatial pattern is fully reproduced in the present MMCR radar dataset as shown in Section 3.1 and Figure 3c, two-layer cloud fractions show negligible east-west spatial divergence nationwide. By contrast, single-layer clouds occur much more frequently across arid northwest China (Fig. 3b), while multi-layer clouds (defined as systems with three or more layers in the present study) are concentrated over humid southeastern regions (Fig. 3d). The consistent spatial signatures retrieved from both radiosonde and radar observations verify that two-layer clouds constitute a unique transitional cloud regime. This spatial decoupling—where two-layer clouds behave as a transitional regime between the other two categories—would be completely obscured if we adopted a simple binary classification (single-layer vs. all clouds with ≥ 2 layers). Separating two-layer clouds thus preserves a distinct observational signature that is consistently captured by two independent observing systems.

Physically, two-layer and multi-layer clouds arise from different processes. Two-layer clouds frequently result from decoupling of the cloud-topped boundary layer, where the surface mixed layer separates from the overlying cloud deck, forming a stable interface between them (Bretherton and Wyant, 1997; Wyant et al., 1997). This allows the lower and upper layers to respond to different thermodynamic controls. In contrast, multi-layer clouds (≥ 3 layers) are more commonly associated with organized deep convection or frontal systems, where multiple cloud layers coexist within a single dynamically coupled structure. Merging these two categories would conflate clouds formed by boundary-layer decoupling with those embedded in deep convective or baroclinic systems, weakening the physical interpretability of our classification.

For these reasons, we retained the three-category classification in Figure 3 and clarified the scientific motivation at the end of Section 3.1, as follows:

“We separate two-layer from multi-layer clouds (≥ 3 layers) because they exhibit distinct spatial patterns and formation mechanisms. Two-layer clouds lack a clear regional preference in both a previous global radiosonde study (Xu et al., 2023) and the present MMCR observations (Fig. 3c,d), confirming their transitional nature. Physically, two-layer clouds often result from boundary-layer decoupling (Bretherton and Wyant, 1997), whereas multi-layer clouds are more typical of organized deep convection or frontal systems. Merging these categories would conflate dynamically distinct cloud populations.”

References:

- Xu, H., Guo, J., Tong, B., Zhang, J., Chen, T., Guo, X., Zhang, J., and Chen, W.: Characterizing the near-global cloud vertical structures over land using high-resolution radiosonde measurements, *Atmos. Chem. Phys.*, 23, 15011–15038, <https://doi.org/10.5194/acp-23-15011-2023>, 2023.
- Bretherton, C. S., and Wyant, M. C.: Moisture transport, lower-tropospheric stability, and decoupling of cloud-topped boundary layers, *J. Atmos. Sci.*, 54, 148–167, [https://doi.org/10.1175/1520-0469\(1997\)054<0148:MTLTSA>2.0.CO;2](https://doi.org/10.1175/1520-0469(1997)054<0148:MTLTSA>2.0.CO;2), 1997.

Specific comments:

1. Line 166: Please clarify what is meant by “valid observation days”. Does this refer to days with continuous/full-day radar observations, or days that meet a minimum data availability threshold? If a threshold was used, please specify it.

Response: In our data processing, a “valid observation day” is defined as a calendar day with at least 8 hours of valid MMCR measurements. This threshold ensures that the daily data are sufficiently representative of the diurnal cloud cycle while excluding days with major instrument maintenance, system malfunctions, or incomplete data records due to power outages or communication failures.

To avoid ambiguity, we have added a clear definition of “valid observation days” in the revised manuscript in Section 2.2.1 as follows:

“Of the 120 MMCR stations operating across China in 2024, only those with at least 100 valid observation days annually (defined as calendar days with at least 8 hours of valid MMCR measurements) were retained to ensure data quality. This criterion resulted in the selection of 80 stations for subsequent analysis (Fig. 1).”

2. Please clarify whether radar wind profiler data were used during precipitation periods. If so, how were precipitation-contaminated periods handled? The reliability of RWP retrievals can vary substantially under clear-sky, cloudy, and precipitation conditions. Please discuss how the authors assessed the trustworthiness of RWP

observations under these different conditions, and whether any filtering or quality flags were applied before using the data in the analysis.

Response: We thank the reviewer for this important technical question. In our analysis, RWP data during precipitation periods were excluded to avoid contamination of the wind shear calculation.

The quality control of RWP data used in this study includes the following procedures: (1) within each profile over the 0.5-5.0 km height range, missing values and significant outliers exceeding 2.5 standard deviations from the mean were removed; (2) if more than 40% of the data points within this height range were outliers or missing, the entire profile was discarded; (3) discontinuous or missing data points were estimated using linear interpolation; and (4) observations were restricted to the 0.5 – 5.0 km height range to avoid near-surface clutter and beam attenuation, ensuring the accuracy of VWS calculations.

We have added a brief clarification in Section 2.2.2 of the revised manuscript. The added text reads as follows:

“Before deriving VWS from the RWP measurements, we applied a multi-step quality control procedure following Wei et al. (2014) and Miao et al. (2018). First, data during precipitation periods were excluded to avoid contamination from precipitation particles, which can introduce significant errors in Doppler-based wind retrieval. Second, within each profile over the 0.5-5.0 km height range, missing values and outliers exceeding 2.5 standard deviations from the mean were removed. Third, if more than 40% of the data points within this height range are outliers or missing, the entire profile was discarded. Fourth, discontinuous or missing data points were estimated using linear interpolation. Fifth, only observations within the 0.5-5.0 km height range were retained to avoid near-surface clutter and beam attenuation. The resulting quality-controlled RWP data were then used to calculate VWS according to Eq. (1) at the appropriate pressure level (700 hPa for stations with elevation < 3 km, and 500 hPa for stations with elevation $\geq$ 3 km). ”

References:

- Miao, Y., Guo, J., Liu, S., Wei, W., Zhang, G., Lin, Y., and Zhai, P.: The Climatology of Low-Level Jet in Beijing and Guangzhou, China, *J. Geophys. Res.-Atmos.*, 123(5), 2816–2830, <https://doi.org/10.1002/2017jd027321>, 2018.
- Wei, W., Zhang, H. S., and Ye, X. X.: Comparison of low-level jets along the north coast of China in summer, *J. Geophys. Res.-Atmos.*, 119(16), 9692–9706, <https://doi.org/10.1002/2014jd021476>, 2014.

3. Line 187: The manuscript should provide more details on the quality control procedures applied to the observations. For example, what types of artifacts were removed? Were thresholds applied to signal-to-noise ratio, reflectivity, velocity, or

other radar moments? Were insects, precipitation, ground clutter, or non-meteorological echoes filtered? Were quality flags provided by the instrument data stream used? Because cloud vertical structure statistics can be sensitive to radar sensitivity and QC choices, a more detailed description is needed to make the results reproducible and interpretable.

Response: We thank the reviewer for this detailed and constructive comment regarding the quality control procedures applied to the observations. We agree that the original manuscript lacked sufficient details on the QC procedures for the RWP data. To address this, we have made the following revisions:

First, we have expanded the description of RWP quality control in Section 2.2.2. as in the previous Response,

“Before deriving VWS from the RWP measurements, we applied a multi-step quality control procedure following Wei et al. (2014) and Miao et al. (2018). First, data during precipitation periods were excluded to avoid contamination from precipitation particles, which can introduce significant errors in Doppler-based wind retrieval. Second, within each profile over the 0.5-5.0 km height range, missing values and outliers exceeding 2.5 standard deviations from the mean were removed. Third, if more than 40% of the data points within this height range are outliers or missing, the entire profile was discarded. Fourth, discontinuous or missing data points were estimated using linear interpolation. Fifth, only observations within the 0.5-5.0 km height range were retained to avoid near-surface clutter and beam attenuation. The resulting quality-controlled RWP data were then used to calculate VWS according to Eq. (1) at the appropriate pressure level (700 hPa for stations with elevation < 3 km, and 500 hPa for stations with elevation $\geq$ 3 km). ”

Second, regarding the MMCR data, we note that the QC procedures are already detailed in Section 2.3 of the revised manuscript. These include: (1) the height-dependent NER threshold (Eq. 4) to remove random instrumental noise; (2) the variance-based clutter suppression method (Kalapureddy et al., 2018) using $\mu < 2.0$ dBZ and $\sigma < 1.0$ dBZ to distinguish cloud signals from non-meteorological clutter (including ground clutter, insects, and turbulence-induced echoes); (3) the -20 dBZ reflectivity filter to exclude residual noise or sub-detection-limit echoes; and (4) thin-layer merging/removal rules (210 m thickness threshold and 720 m separation threshold) to reduce artificial layer fragmentation. These thresholds are consistent with established practices in Ka-band cloud radar studies (Clothiaux et al., 1999; Kalapureddy et al., 2018; Zhang et al., 2019).

4. ERA5 data have an hourly temporal resolution. Did the authors average or aggregate the MMCR observations to hourly resolution before matching them with ERA5? Please describe the temporal matching procedure clearly.

Response: We thank the Reviewer for this question. Prior to correlation analysis, we aggregated the original 1-minute MMCR observations to an hourly resolution and spatially matched them to the nearest ERA5 grid cell.

Specifically, for each station and each UTC hour, we calculated the hourly mean CBH, CTH, and cloud thickness (CT) from all valid 1-minute samples within that hour. The corresponding ERA5 variables (2 m specific humidity and lower-tropospheric stability) were extracted at the same UTC hour from the closest ERA5 grid point to the station. All subsequent correlation and joint-dependence analyses were performed on these fully synchronized, spatiotemporally matched hourly pairs.

We have added a full description of this procedure in Section 2.3 as follows:

“With validated cloud boundaries in hand, we then prepared the data for correlation analysis. To ensure spatiotemporal consistency between the MMCR retrievals and ERA5 reanalysis, the 1-minute MMCR observations were first aggregated into hourly means of CBH, CTH, and CT. For each station, ERA5 meteorological variables were extracted at the corresponding UTC hour from the nearest grid point. All correlation and joint dependence analyses were subsequently conducted on these fully synchronized, spatiotemporally matched hourly paired datasets.”

5. Line 223: The authors compare the detection limit of the China Ka-band cloud radars with ARM Ka-band radar observations. However, radar sensitivity depends strongly on hardware settings, calibration, operating mode, antenna configuration, pulse length, integration time, and processing algorithms. Please clarify how the authors confirmed that the detection limits are comparable between the ARM Ka-band radar and the China radar network. Were instrument specifications, calibration documents, or sensitivity estimates used? If not, the authors should be more cautious in making this comparison.

Response: We thank the reviewer for this careful observation. We apologize that our original wording may have inadvertently implied a direct comparison between of detection limits between the ARM MMCR and the China MMCR network. This was not our intention.

We referenced Clothiaux et al. (1999) solely to introduce the reflectivity threshold method and to explain why subsequent studies (e.g., Zhang et al., 2019; Chen et al., 2022; Fang et al., 2023) commonly adopt a threshold near -40 dBZ. It is a foundational paper documenting the typical reflectivity range of various cloud types

observed by Ka-band cloud radars, not a comparison of instrument sensitivity between systems.

To remove any ambiguity, we have revised the relevant sentence in the manuscript as follows (Section 2.3):

“In the literature, the reflectivity threshold method is a widely used approach for distinguishing cloud signals from background noise and clutter using a fixed reflectivity cutoff. Based on the operational characteristics of MMCR, Clothiaux et al. (1999) reported that radar reflectivity (Z) for cirrus, stratus, and precipitating clouds typically ranges from –50 dBZ to 20 dBZ. Consequently, many previous studies have adopted a constant minimum threshold of approximately –40 dBZ for cloud detection (e.g., Zhang et al., 2019; Chen et al., 2022; Fang et al., 2023).”

This revision clarifies that Clothiaux et al. (1999) serves as a general literature reference for the reflectivity range of cloud targets, rather than as a specific instrument comparison. We appreciate the reviewer’s suggestion, which has helped us improve the precision of our manuscript.

6. Line 295: I do not fully agree with the interpretation that the lower radar-derived cloud fraction relative to the MODIS long-term mean necessarily reflects a declining trend in total cloud fraction over East Asia. This difference could also be related to fundamental differences between observing systems.

Response: We thank the Reviewer for this important comment. We agree that our original interpretation placed undue emphasis on the long-term declining trend in cloud fraction over East Asia, without adequately acknowledging the fundamental differences between the two observing systems.

In the revised manuscript (Section 3.1), we have adopted a more balanced perspective that clearly delineates both contributing factors, as follows:

“This value is slightly lower than the long-term mean cloud fraction of approximately 61% derived from MODIS observations during 2003–2018 (Zhao et al., 2019). Two factors may contribute to this disparity. First, the two quantities are not directly equivalent: MMCRs measure point-scale temporal cloud occurrence, whereas MODIS reports grid-averaged areal cloud fraction, and this fundamental difference warrants caution in quantitative comparisons. Second, the documented declining trend in cloud cover over East Asia (Zhou et al., 2022) may account for part of the offset, given that our 2024 observations represent a more recent period than the MODIS climatology. The relative contribution of this trend, however, cannot be isolated from the inherent observational differences.”

7. Line 318: The authors correctly state that satellite products represent areal cloud fraction over large grid cells, whereas MMCR measurements capture local, vertically

resolved cloud occurrence. This is an important point. However, this also means that the manuscript should be very cautious when comparing satellite cloud fraction with MMCR-derived temporal cloud fraction. These two quantities are not directly equivalent. I suggest revising the relevant discussions.

Response: We thank the reviewer for this thoughtful and constructive comment. We fully agree that satellite-derived areal cloud fraction and MMCR-based temporal cloud occurrence are not directly equivalent quantities, and that any cross-platform comparison must be made with explicit caution.

In the revised manuscript, we have carefully revisited all such comparisons and added clarifying statements, as follows:

For the comparison of national mean values (Section 3.1): We have replaced the original one-sided attribution to a long-term trend with a balanced discussion that explicitly acknowledges the fundamental differences between the two data types. The revised text now reads:

“Two factors may contribute to this disparity. First, the two quantities are not directly equivalent: MMCRs measure point-scale temporal cloud occurrence, whereas MODIS reports grid-averaged areal cloud fraction, and this fundamental difference warrants caution in quantitative comparisons. Second, the documented declining trend in cloud cover over East Asia (Zhou et al., 2022) may account for part of the offset, given that our 2024 observations represent a more recent period than the MODIS climatology. The relative contribution of this trend, however, cannot be isolated from the inherent observational differences.”

8. Line 326: The discussion in this section relies mostly on citing previous studies. I suggest adding more analysis.

Response: We thank the reviewer for this constructive suggestion. To strengthen the analysis in Section 3.1, we have added additional quantitative analysis, as follows:

“Single-layer clouds occur more frequently in northwestern China relative to southeastern regions (Fig. 3b), with the most substantial regional disparities in single-layer cloud frequency concentrated over arid inland basins and the Inner Mongolian Plateau. Multi-layer clouds show an opposite spatial tendency: their occurrence is consistently more prevalent throughout southeastern China than across inland northwestern areas (Fig. 3d). This regional divergence likely reflects differences in moisture availability and atmospheric instability. Southeastern China, influenced by abundant water vapor transport and intense solar heating, both of which favor deep convection and the development of vertically complex, multi-layered cloud system (Chi et al., 2022). By comparison, dry, stable boundary-layer conditions in northwestern China suppress vertical motion and cloud development, leading to single-layer clouds dominant (Chen et al., 2019).

Two-layer cloud occurrence lacks a clear east-west or north-south spatial gradient nationwide (Fig. 3c), with only mild regional disparities in average occurrence separating southeastern and northwestern monitoring domains. This uniform distribution indicates two-layer clouds act as an intermediate transitional state between two dominant cloud regimes, and indicating that the transition from single-layer to multi-layer cloud systems cannot be described by a simple additive relationship. We separate two-layer from multi-layer clouds (≥ 3 layers) because they exhibit distinct spatial patterns and formation mechanisms. Two-layer clouds lack a clear regional preference in both a previous global radiosonde study (Xu et al., 2023) and the present MMCR observations (Fig. 3c,d), confirming their transitional nature. Physically, two-layer clouds often result from boundary-layer decoupling (Bretherton and Wyant, 1997), whereas multi-layer clouds are more typical of organized deep convection or frontal systems. Merging these categories would conflate dynamically distinct cloud populations. ”

9. The authors state that cloud-base height is important for regional weather forecasting and climate change assessment, but this point needs clearer explanation. Please describe more specifically why CBH matters.

Response: We thank the Reviewer for this suggestion. In the revised manuscript, we have expanded the explanation of why CBH matters, grounding it in specific physical mechanisms and quantitative radiative sensitivities.

The revised text in Section 3.2 now reads:

“CBH, CTH, and CT are fundamental descriptors of cloud vertical structure. Among these, CBH is particularly critical because of its role in modulating surface radiation and turbulent energy exchange, and because it serves as a key link between surface–atmosphere interactions and cloud formation. Dynamically, it influences the initiation and evolution of convective precipitation in numerical weather prediction models (Haliczer et al., 2025). Radiatively, it serves as a key variable for surface energy budget assessment: the cloud radiative effect at the surface decreases with increasing CBH at a rate of approximately $4\text{--}5\text{ W m}^{-2}$ per km at mid-latitude sites (Viúdez-Mora et al., 2015). Even modest uncertainties in CBH can produce substantial radiative biases—an uncertainty of 100 hPa in mid-level cloud base pressure can cause errors of at least 10 W m^{-2} in surface net longwave radiation (Fung et al., 1984), and smaller variations at lower levels can yield even larger uncertainties. Accurate CBH observations are therefore essential for quantifying cloud feedbacks in a changing climate (Zelinka and Hartmann, 2010; Costa-Surós et al., 2013).”

References:

- Costa-Surós, M., Calbó, J., González, J.A., and Martin-Vide, J.: Behavior of cloud base height from ceilometer measurements, *Atmos. Res.*, 127, 64–76, <https://doi.org/10.1016/j.atmosres.2013.02.005>, 2013.
- Fung, I.Y., Harrison, D.E., and Lacis, A.A.: On the variability of the net longwave radiation at the ocean surface, *Rev. Geophys.*, 22, 177–193, <https://doi.org/10.1029/RG022i002p00177>, 1984.
- Haliczer, D.T., Mecikalski, J.R., and Kollias, P.: Use of satellite, surface observations and numerical weather prediction model data to improve cloud base height and cloud base vertical velocity estimation, *J. Geophys. Res.-Atmos.*, 130, e2024JD041853, <https://doi.org/10.1029/2024JD041853>, 2025.
- Valdez-Mora, A., Costa-Surós, M., Calbó, J., and González, J.A.: Modeling atmospheric longwave radiation at the surface during overcast skies: The role of cloud base height, *J. Geophys. Res.-Atmos.*, 120, 199–214, <https://doi.org/10.1002/2014JD022310>, 2015.
- Zelinka, M.D., and Hartmann, D.L.: Why is longwave cloud feedback positive? *J. Geophys. Res.*, 115, 1–16, <https://doi.org/10.1029/2010JD013817>, 2010.

10.Line 390: Please check the citation of Shupe et al. 2011. I guess that Shupe et al. focused primarily on Arctic (or high-latitude) cloud observations. If so, the citation may not be directly applicable to mid-latitude or China-region cloud regimes.

Response: We thank the Reviewer for this careful check. The Reviewer is correct that Shupe et al. (2011) focused on Arctic clouds. We agree that citing an Arctic-specific study to support a mid-latitude finding over China is inappropriate. We have therefore replaced the citation with studies directly relevant to the China region.

The sentence was revised as follows:

“This seasonal progression is consistent with previous studies (e.g., *Zhang et al.*, 2018; Chi et al., 2022; Xu et al., 2023) and reflects the strong modulation of cloud formation by radiative forcing and boundary-layer dynamics.”

Reference:

- Zhang, Y., Zhang, L. J., Guo, J. P., Feng, J. M., Cao, L. J., Wang, Y., Zhou, Q., Li, L. X., Li, B., Xu, H., Liu, L., An, N., and Liu, H.: Climatology of cloud-base height from long-term radiosonde measurements in China, *Adv. Atmos. Sci.*, 35, 158–168, <https://doi.org/10.1007/s00376-017-7096-0>, 2018.