Responses to reviewer comments

In this response letter, we provide a point-by-point response to each comment. The original comments are in *blue italic font*, and our response are in black font. Changes made in the manuscript are listed in quotes with line numbers of the tracked changes version.

Reviewer #1:

General comments:

The authors employ high-resolution near-LES WRF simulations to investigate aerosol-cloud interactions (ACI) in marine boundary layer (MBL) clouds over the Eastern North Atlantic (ENA). The study is methodologically rigorous, leveraging satellite retrievals, ground-based ARM observations, and process-level diagnostics (e.g., CFODD analysis). The conclusions highlight persistent model-observation discrepancies in LWP susceptibility, particularly for non-precipitating thick clouds, and propose mechanistic explanations tied to precipitation efficiency and entrainment biases. The paper is well-organized and addresses a critical gap in ACI understanding. However, several scientific and methodological issues require clarification to ensure robustness.

Major comments:

- *Section 3.1 evaluates two representative cases by Meteosat; however, the Meteosat data shows dissipation and reformation processes that the model didn't capture. I expected the authors to focus on the discrepancy and discuss the reason for this mismatch, but I couldn't find any direct discussion on this. In some paragraphs, the authors point out model bias in LWP susceptibility to aerosols, which is good, but still, the model bias in Section 3.1 needs explanations.*

Thanks for your question. The lack of cloud dissipation and diurnal variation in marine boundary layer (MBL) clouds in the WRF model is likely associated with the biases in the thermodynamic profiles inherited from ERA5. As seen in Figures R1 left figure, on 21 July 2016, ARM sounding observations indicate a sharp decrease in moisture above the PBL between 14 and 20 UTC, leading to the dissipation of clouds after 14 UTC (Figure 1a). In contrast, both ERA5 and WRF simulation show a gradual decrease in specific humidity and relative humidity above the PBL from 0 to 20 UTC, resulting in a much moister layer above clouds in the model (Figures R1 middle and right). Consequently, clouds did not dissipate in the afternoon in the simulation.

On 25 July 2016, the ARM sounding observations similarly exhibit a pronounced decrease in specific humidity and relative humidity above the PBL between 14 and 24 UTC (Figure R2). In this case, the WRF simulation accurately capture the observed feature, reproducing a sharp decrease in moisture above the PBL from 14 to 24 UTC. As a result, clouds in the N=100 and N=1000 simulations dissipate from 14 to 24 UTC, consistent with satellite observation (Figure R3). This pattern also holds for other cases in the high-ridge regime, such as 22 and 28 July 2016, where the accuracy of the simulated PBL moisture variation determined whether the model captured the observed diurnal evolution of clouds (figures not shown). These cases demonstrate that the diurnal cycle of cloudiness is highly sensitive to the representation of diurnal variation in moisture as well as the moisture gradients near the inversion.

The fixed, vertically uniform aerosol concentration further contributes to the persistence of clouds by maintaining unrealistically high CCN concentrations throughout the day and suppressing precipitation. The lack of precipitation scavenging also reduces evaporative cooling and weakens cloud–PBL decoupling, inhibiting afternoon cloud breakup.

We added these discussions to the second last paragraph in Section 3.1:

“The absence of afternoon cloud dissipation in WRF simulations are likely associated with model biases in the thermodynamic structure inherited from ERA5. For example, on 21 July 2016, ARM sounding observations show a pronounced decrease in specific humidity and relative humidity above the PBL between 14 and 20 UTC (figures not shown). This sharp drying leads to cloud erosion in the observations. However, WRF simulations or ERA5 reanalysis produces only a gradual reduction in moisture from 00 to 20 UTC (Figure 2a), maintaining a moist layer above cloud top and prevent cloud breakup. On 22 July 2016, the model reproduces the moisture gradient above PBL with a warm and dry layer above, the lifted cloud top in the N=1000 simulation entrain dry air into cloud system and dissipate clouds in the afternoon (Figure 3a). On days when ERA5 accurately capture the observed moisture decrease above PBL (e.g., 25 and 28 July 2016), the model reproduces both the dissipation and evening redevelopment of clouds seen in Meteosat data (figures not shown). This indicates that the diurnal evolution of MBL clouds is highly sensitive to the representation of diurnal variation in moisture as well as the moisture gradients near the inversion.

The prescribed, vertically uniform aerosol concentration further reinforces cloud persistence by maintaining elevated CCN levels and suppressing drizzle formation. The lack of precipitation scavenging prevents cloud-base evaporative cooling and inhibits decoupling, both of which would otherwise promote afternoon cloud breakup. The implications of thermodynamic and aerosol-related biases for the estimated ACI are discussed in detail in Section 3.3.2. (Lines 436-455)”

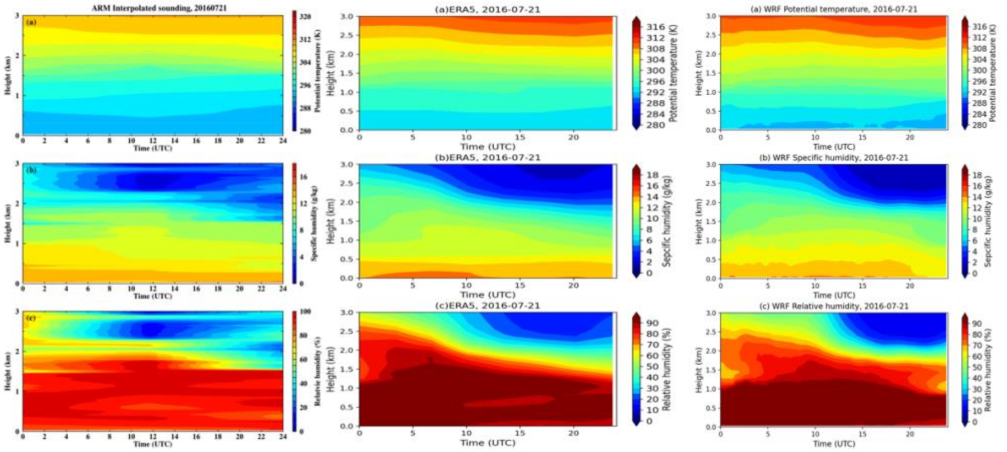

Figure R1 Time series of thermodynamic profiles on 21 July 2016, for (a) potential temperature (unit: K) (b) specific humidity (unit g/kg), (c) relative humidity in (left) ARM interpolated sounding, (middle) ERA5 reanalysis, and (right) in WRF N=100 simulation.

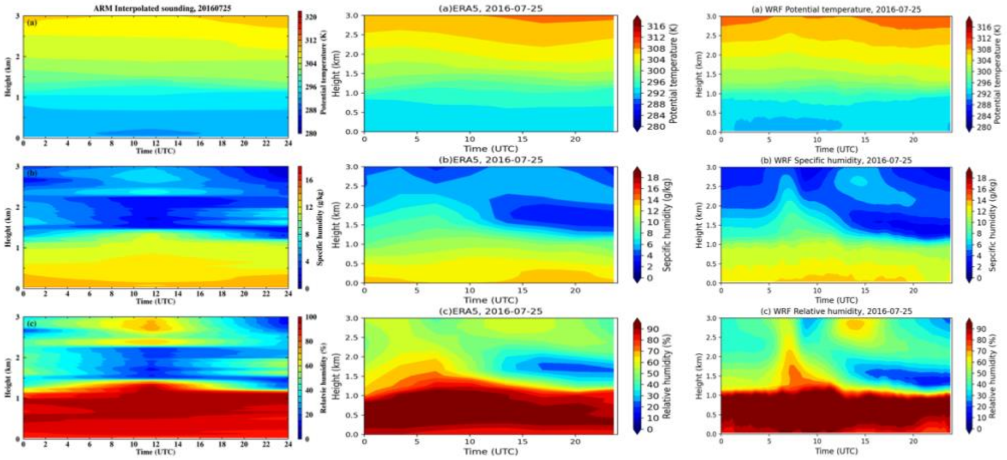

Figure R2 Same as Figure R1 but for the case on 25 July 2016.

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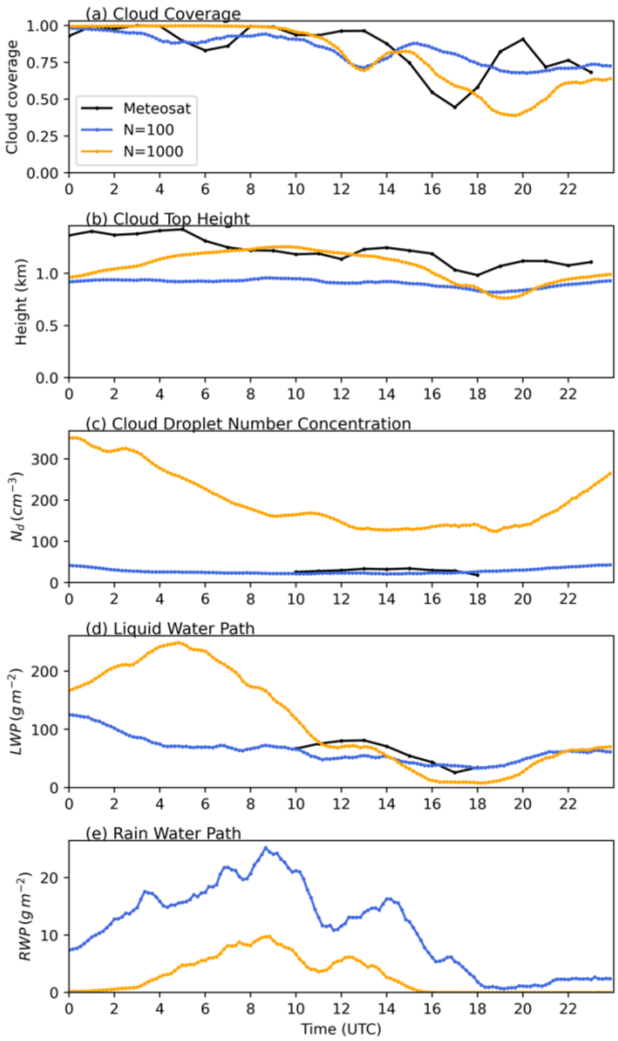

Figure R3. Time series of domain-averaged cloud properties from observations and model simulation on 25 July 2016. (a) Cloud coverage, (b) cloud top height, (c) cloud liquid water path, and (d) rain-water path for N=100 (blue lines) and N=1000 (orange lines) experiments.

- *Paragraph in Lines 395: the authors use 15 microns as the threshold to differentiate precipitating clouds and non-precipitating clouds. Since the authors have very good representative cases with one precipitating and another not, why not separate the two scenarios by cases? I believe the authors know the threshold is a bit tricky because other values (12 microns or 13 microns) have been used in previous literature, and so far, we don't have an agreement on which number is best.*

Thanks for the suggestion. We didn't separate the non-precipitating and precipitating scenarios by cases because most cases have clouds transitioned from one to another during the simulation period. Instead, we classify cloud state at each time step. We use the 15-micron threshold in the model to be consistent with the precipitation threshold used in the satellite observations. As the main goal of this study is to explain the discrepancy between the observed and simulated LWP susceptibility, we use the same classification of precipitation in the model as in the satellite observation to make consistent comparison. In Figure 6d, we evaluated the 15-micron threshold in the model using the column maximum radar reflectivity ($Z\ \ max$) greater than -15 dBZ at each model output time. As shown in Figure 6d, model generates precipitation too often at smaller drop size with $r_e > 10\ \mu m$ and at higher N_d concentration. The over-estimation of precipitation in the model is the leading cause of the positive bias in LWP susceptibility.

We agree that the threshold of 15-micron could be tricky and different threshold values have been used in previous studies. In our previous satellite observational study, we evaluated different effective radius thresholds and rain rate thresholds in satellite retrievals using precipitation masks derived from ground-based radar reflectivity at the ENA site, and we found that the $r_e > 15\ \mu m$ threshold showed the best agreement with ground-based observations (Qiu et al., 2024). To address this comment, and a similar comment from the other reviewer, we add the definitions of different cloud states:

"Based on the relationships between r_e, LWP, and N_d in the satellite retrievals (e.g., $LWP = \frac{4r_e\tau}{3Q_{ext}}$, $N_d = \frac{\sqrt{5}}{2\pi k}(\frac{f_{ad}c_w\tau}{Q_{ext}\rho_w r_e^5})^{1/2}$), r_e =15 isolines is marked in the LWP-N_d parameter space as an commonly used indicator of precipitation likelihood in the satellite retrieval (e.g., Gryspeerdt et al., 2019; Toll et al., 2019; Zhang et al., 2022; Qiu et al., 2024). Based on the distinct LWP, cloud albedo and CF susceptibilities, MBL clouds are classified into three states: the precipitating clouds (r_e >15 μm), the non-precipitating thick clouds (r_e <15 μm, LWP> 75 gm^{-2}), and the non-precipitating thin clouds (r_e <15 μm, LWP< 75 gm^{-2}) (Qiu et al., 2024). To be consistent with observational reference, the WRF simulated cloud states are classified using the same definition. (Lines 479-487)"

- *LWP Susceptibility Discrepancy (Lines 417–419)*
The model shows a positive LWP response (+0.32) for non-precipitating thick clouds, while observations show a strong negative response (-0.69). What is the primary driver of this discrepancy?

Thanks for your question. We added more explanation in the summary paragraph of section 3.2 to address this comment:

"Large discrepancies remain for non-precipitating or lightly drizzling thick clouds, where the model simulates too many polluted thick clouds and yields an opposite (positive) LWP response compared to the strongly negative satellite signal.

In addition, the model-observation discrepancy persists across all synoptic regimes, suggesting that they originate from the model's representation of cloud microphysics, precipitation, and aerosol-cloud coupling rather than from large-scale meteorological variability. The robustness of these modeled LWP response, consistent with previous LES studies of similar cloud regimes (e.g., Wang et al., 2020; Lee et al., 2025), further motives the central focus of the next section: diagnosing the physical mechanisms driving these biases. We show that three leading factors dominate the discrepancy: excessive precipitation production in thick clouds, a moist bias above cloud top, and satellite retrieved N_d-LWP relationships contaminated by internal cloud processes. (Lines 592-608)"

- *Model Biases and Initial Conditions (Lines 356-360, 642-664)*
The study identifies biases in ERA5 reanalysis (e.g., underestimated PBL height, overestimated cloud-top RH) as a significant source of discrepancy. However, the extent to which these biases propagate into the WRF simulations and affect ACI estimates is not fully quantified. Sensitivity tests using alternative reanalysis datasets or perturbed initial conditions could help isolate the impact of these biases. If perturbed simulations or using different reanalysis datasets add too much work, at least discussion on this point is necessary.

Thanks for the insightful question and suggestion. As seen in Figure 11, the cloud-top RH in WRF simulations is ~ 8% higher than ARM observation. Based on the relationships between cloud-top RH against LWP and CF susceptibilities, the 8% wet bias may lead to an overestimation of 0.04 and 0.005 in LWP and CF susceptibility, respectively (Figure R4). Similarly, LWP and CF susceptibilities positively correlate with cloud top height (Figure R5). As seen in Figure R6, due to the under-estimation of PBL height in ERA5 reanalysis and WRF simulations, the simulated cloud top is ~480 m lower than Meteosat retrievals. This under-estimation may lead to an ender-estimation of LWP and CF susceptibility of 0.18 and 0.02, respectively. To conclude, the under-estimation of cloud-top height in WRF simulations may exhibit larger impact on LWP susceptibility than the overestimation of clout-top RH, due to the larger bias in cloud-top height between simulations and observations. We have added the following discussions to the manuscript.

"Based on the relationship between cloud susceptibility and cloud-top RH, the over-estimated cloud-top RH may lead to an overestimation of 0.04 and 0.005 in LWP and CF susceptibility, respectively. Meanwhile, the under-estimated cloud-top height of 480 m could result in an under-estimation of LWP and CF susceptibility of 0.18 and 0.02, respectively (figures not shown). Future modeling studies over the ENA region need to improve the initial and boundary conditions, e.g., through data assimilations. (Lines 890-895)"

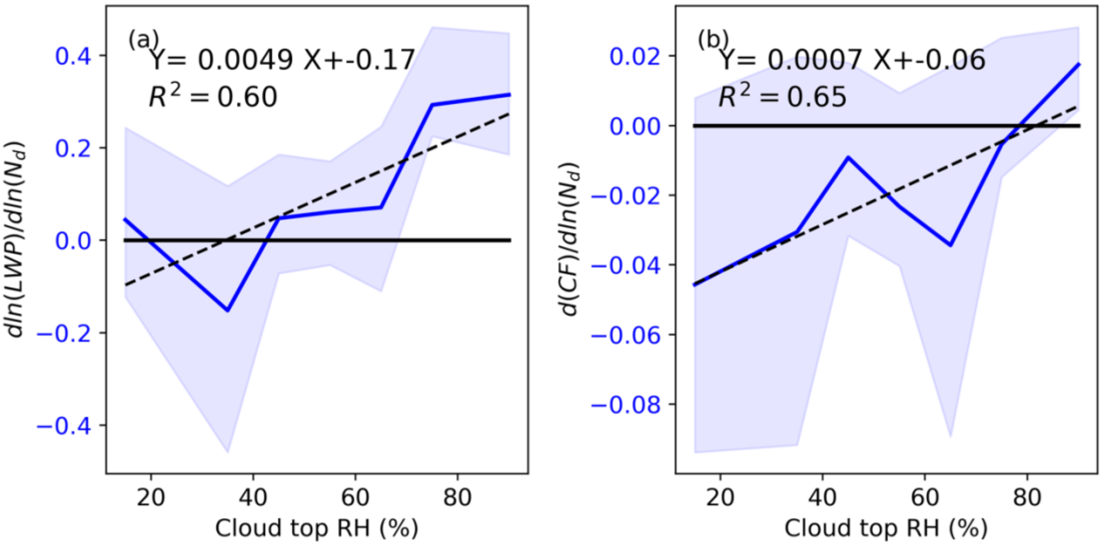

Figure R4. Dependence of (a) LWP susceptibility (b) CF susceptibility on cloud-top relative humidity in WRF simulations during the daytime. The solid blue line shows the median value of each RH bins and the shaded area shows the lower and upper 25th percentiles.

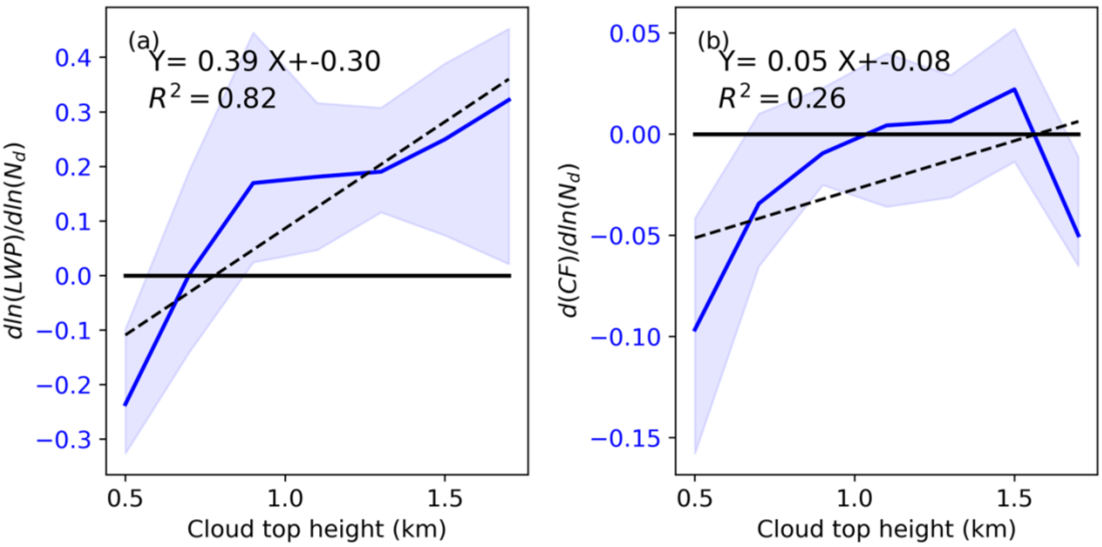

Figure R5. Dependence of (a) LWP susceptibility (b) CF susceptibility on cloud-top height in WRF simulations during the daytime. The solid blue line shows the median value of each RH bins and the shaded area shows the lower and upper 25th percentiles.

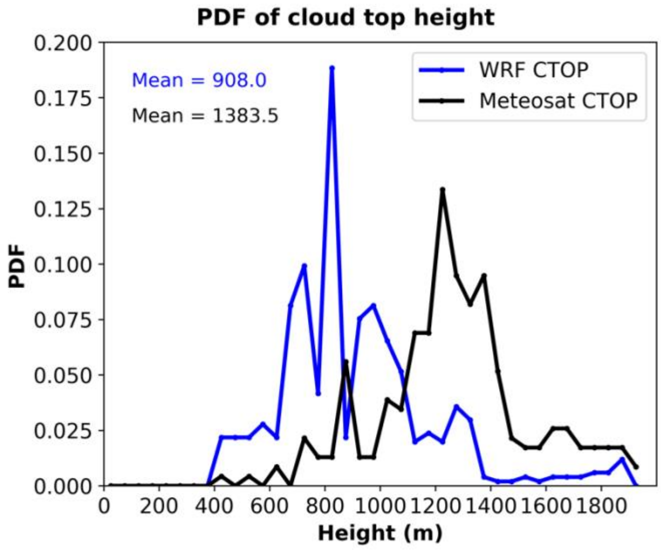

Figure R6. Dependence of (a) LWP susceptibility and (b) CF susceptibility on cloud top height in WRF simulations during the daytime. The solid blue line shows the median value of each RH bins and the shaded area shows the lower and upper 25th percentiles.

- *Precipitation Parameterization (Lines 540-560, 621-628)*

The overestimation of precipitation in thick clouds is attributed to autoconversion, accretion, and DSD issues. While the analysis is thorough, the study could benefit from testing alternative microphysics schemes (e.g., P3, Thompson) to assess the robustness of the conclusions. At lease, I suggest to add discussions on the choice of microphysical schemes and parameters.

Thank you for the insightful question. We added a paragraph on discussion of microphysics scheme at the end of Section 3.3.1:

"While our analysis focuses on the two-moment Morrison scheme, Christensen et al. (2024) found that the choice of microphysics and PBL schemes accounts for only about 30 % of the variability in simulated ACI, much smaller than the variability across meteorological conditions and cloud states. Since this study encompasses 11 cases spanning diverse synoptic regimes and cloud types, the overall conclusions are unlikely to change substantially with alternative two-moment bulk microphysics schemes. Nonetheless, future investigations using multiple microphysics schemes would be valuable for quantifying the robustness of the precipitation parameterization and its role in ACI uncertainty. (Lines 837-844)"

- *Internal Cloud Processes vs. ACI (Lines 684-737)*

The discussion on internal cloud processes (e.g., updraft-driven -LWP relationships) is insightful but could be strengthened by explicitly separating these effects from true ACI in the observational analysis. For example, using conditional sampling (e.g., stratifying by updraft strength) might help disentangle these contributions.

Thanks for the suggestion. In satellite observations, it is a bit challenging to disentangle the N_d-LWP relationships contributed by internal cloud processes from the true ACI, and we don't have direct measurements or retrievals of the cloud base updraft speed or other direct measurement indicating internal cloud processes. To compensate for this limitation in observations, we used model outputs to quantify the N_d-LWP relationships contributed by internal cloud processes in section 3.3.3. We added a sentence to clarify this: "Diagnosing these internal cloud processes in satellite observations is difficult because key governing variables, such as cloud-base updraft speed, TKE, entrainment rate are not directly measured or retrieved. In contrast, model simulations allow us to quantify the N_d–LWP relationships driven by internal cloud processes by examining their spatial covariation under homogeneous aerosol conditions at each timestep. (Lines 930-933)"

- *Case Selection and Representativeness (Lines 232-264)*
The 11 cases span different synoptic regimes, but the rationale for selecting these specific cases (e.g., why not include southerly wind conditions?) is not fully explained. A further discussion on the implications of these synoptic differences would be beneficial.

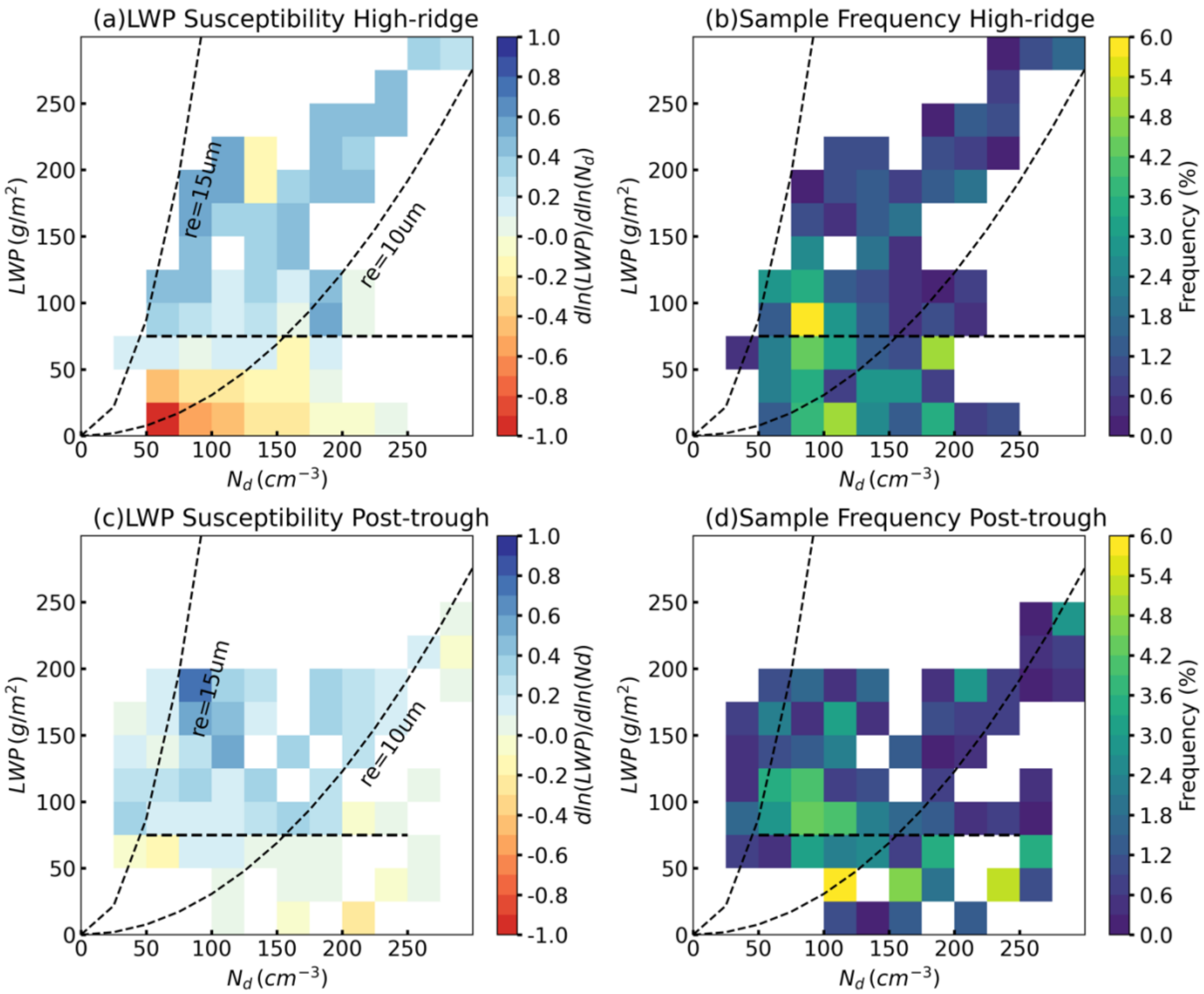

Figure R7. Mean liquid water path (LWP) susceptibility from WRF simulations for (a) (b) the high-ridge regime and (c) (d) the post-trough regime. (a) (c) cloud LWP susceptibility $dln(LWP)/dln(N_d)$, (b) (d) frequency of occurrence of sample in each bin.

Thanks for the question. Previous studies using ARM observations at the ENA site found that aerosol, CCN, cloud properties, and PBL properties are influenced by local emission from the Graciosa Island during southerly wind conditions (e.g., Ghate et al, 2021, 2023). As our study used radar reflectivity profiles at the ARM ENA site to evaluate simulated precipitation processes, we focus on times when the site is dominant by northerly wind from the ocean to minimize influence from the island.

Thanks for the suggestion on adding a discussion on the influence of different synoptic regimes on LWP susceptibility. As we only have one case in the "weak-trough" regime (Table S1), we compared the LWP susceptibility and the occurrence frequency of different cloud states between the "high-ridge" and "post-trough" regimes, as shown in Figures R11.

In our previous study using six-year ground-based observations at the ARM ENA site, Zheng et al. (2025) found that the "high-ridge" regime has significantly more single-layer stratocumulus clouds, thinner cloud depth, smaller LWP, and smaller surface rain rate compared to the "post-trough" regime. Consistent with our previous study, there are more non-precipitating thin clouds in the high-ridge regime compared to the post-trough regime, with the total frequency of occurrence of 49% and 40%, respectively (Figures R11b and d). For cloud susceptibility, the non-precipitating thin clouds in the high-ridge regime exhibit more negative LWP susceptibility compared to clouds with similar LWP and Nd in the post-trough regime, likely due to the cold dry air above clouds with the subsidence in the high-ridge regime. Additionally, the non-precipitating or slightly drizzling thick clouds in both regimes exhibit strong positive LWP susceptibilities, indicating that the model-observation discrepancy for this cloud state is consistent with different synoptic conditions and warrant further investigations in the next section.

We have added Figure R7 to the supplementary information and added the discussion on influence of synoptic regimes on LWP susceptibility to the manuscript:

"To further examine whether these discrepancies depend on large-scale meteorological conditions, we assessed LWP susceptibility across different synoptic regimes. Because only one case is available for the "weak-trough" regime (Table S1), our comparison focuses on the "high-ridge" and the "post-trough" regimes (Figure S10). The "high-ridge" regime shows a higher occurrence of non-precipitating thin clouds than the "post-trough" regime, with total frequencies of 49% and 40%, respectively (Figures S10b, d, t). This more frequent non-precipitating thin cloud in the model is consistent with our previous study based on six years of ground-based observations at the ARM ENA site, which revealed that the "high-ridge" regime favors single-layer stratocumulus clouds with shallower cloud depth and smaller LWP compared to the "post-trough" regime (Zheng et al., 2025).

In addition, non-precipitating thin clouds in the "high-ridge" regime exhibit more negative LWP susceptibilities than clouds with similar LWP and N_d in the "post-trough" regime. This difference in LWP susceptibility is associated with the colder and drier air above clouds under subsidence in the "high-ridge" regime, which enhances cloud dissipation, as also demonstrated in the case study. Overall, non-precipitating or lightly drizzling thick clouds in both synoptic regimes still manifest strong positive LWP susceptibilities, suggesting that the model-observation discrepancy for this cloud state persist regardless of synoptic conditions and therefore warrants further investigation. (Lines 566-583)"

- *Radar Simulator Validation (Lines 214-220, 451-454)*
The use of CR-SIM for radar reflectivity comparison is commendable, but the study does not explicitly validate the simulator against ARM observations for the specific cases analyzed. Including a direct comparison (e.g., scatter plots, statistical metrics) would bolster confidence in the model-observation discrepancies.
Thank you for the valuable suggestion. Figure R8 shows the ARM radar reflectivity profiles for the 11 selected cases. As seen in Figure R8, the radar reflectivity profiles exhibit consistent characteristics as six-year data shown in Figure 7. The only difference is that clouds with $r_e = 5 - 10\ \mu m$ and $\tau > 20$ start drizzling at cloud base for the selected cases (Figure R8i). Therefore, the difference between CR-SIM radar simulator and ARM observations can be attributed to model biases rather than to the representativeness of cases.

We added the following discussion: "To increase the sample size, we analyzed the climate-mean radar reflectivity profiles of stratocumulus and cumulus clouds observed during the summer months (June to August) from 2016 to 2021, comprising a total of 91,737 profiles. Radar reflectivity profiles derived from the selected 11 cases exhibit consistent characteristics (figure not shown). (Lines 662-666)"

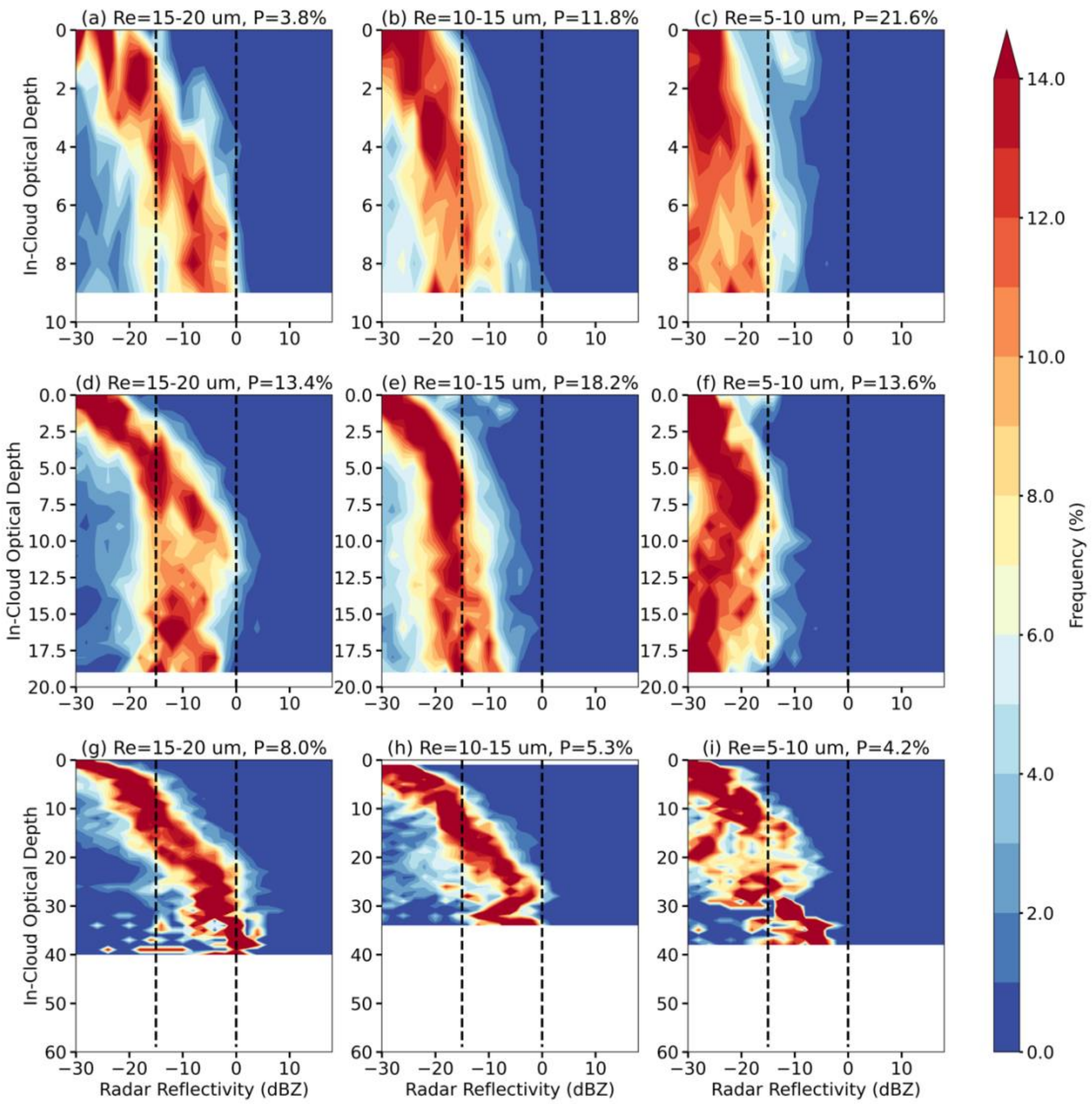

Figure R8. Frequency of radar reflectivity as a function of in-cloud optical depth (τ_d) for ARM ground-based observations during the daytime for the selected 11 cases. Different rows are for different ranges of optical depth (τ): (a)-(c) clouds with $\tau < 10$, (d)-(f) clouds with $10 < \tau < 20$, (g)-(i) clouds with $\tau > 20$. Different columns are for different ranges of effective radius (r_e). The left, middle, and right columns are for $15 - 20\ \mu m$, $10 - 15\ \mu m$, and $5 - 10\ \mu m$, respectively. The black dashed lines in each panel denote -15 dBZ and 0 dBZ, as thresholds of drizzle and rain, respectively. The percentage of sample (P) for each subgroup is denoted in the figure, with a total sample of 4648.

Minor comments:

- *Clarify Terminology (Lines 395-400)*

The term "susceptibility" is used interchangeably for LWP and CF responses. Consider defining these terms more explicitly early in the manuscript (e.g., in the Abstract or Introduction).

Thanks for the suggestion. We have added the definitions of susceptibility and method used to quantify LWP and CF susceptibilities to the method section. "In the context of ACI: cloud susceptibility quantifies how sensitive a cloud property responds to change in aerosol concentration or N_d. To constrain the spatial-temporal variation in meteorological conditions and cloud properties, cloud susceptibility is estimated as the regression slope between N_d and cloud properties within the $1° \times 1°$ domain at each time step of satellite observations. In this study, we quantify both LWP and cloud fraction (CF) susceptibilities to N_d perturbations. Because of the non-linear relations between LWP and N_d, the LWP susceptibility is quantified in logarithm scale as:

$dln(LWP)/dln(N_d)$ (e.g., Gryspeerdt et al. 2019; Qiu et al., 2024) and CF susceptibility is quantified as: $dCF/dln(N_d)$ (e.g., Kaufman et al. 2005; Chen et al., 2022; Qiu et al., 2024). (Lines 169-177)"

- *Equation (1) (Lines 387-394)*

The derivation of N_d from r_e is not fully explained. Briefly clarify the assumptions (e.g., adiabaticity, k value) or cite a reference for the equation.

Following your suggestion, we moved this paragraph to the method section and added the derivations and assumptions for r_e and N_d retrievals to the manuscript:

"In this study, we used the cloud mask, cloud effective radius (r_e), cloud optical depth (τ), cloud liquid water path (LWP), cloud phase, and cloud top height variables in the SEVIRI Meteosat cloud retrieval product (Minnis et al., 2011, 2021). We focus on warm boundary layer clouds with cloud top below 3km and a liquid cloud phase. The r_e and τ retrievals are based on the shortwave-infrared split window technique during the daytime. Cloud LWP is derived from r_e and τ using the equation: $LWP = \frac{4r_e\tau}{3Q_{ext}}$, where Q_{ext} represents the extinction efficiency and assumed constant of 2.0. Cloud mask algorithm is consistent with the CERES Ed-4 algorithm, as described in Trepte et al. (2019), where cloudy and clear pixels are distinguished based on the calculated TOA clear-sky radiance. Cloud top height is derived from the retrieved cloud effective and top temperature, together with the boundary-layer temperature profiles and lapse rate, as described in Sun-Mack et al. (2014). Cloud N_d is retrieved based on the adiabatic assumptions for warm boundary layer clouds, based on the following equation:

$$N_d = \frac{\sqrt{5}}{2\pi k}\left(\frac{f_{ad}c_w\tau}{Q_{ext}\rho_w r_e^5}\right)^{1/2} \qquad (1)$$

In Equation (1), k represents the ratio between the volume mean radius and r_e, and it is assumed to be constant of 0.8 for stratocumulus, f_{ad} is the adiabatic fraction, c_w is the condensation rate, Q_{ext} is the extinction coefficient, and ρ_w is the density of liquid water (Grosvenor et al., 2018). (Lines 148-165)"

- *Statistical Significance (Lines 406-417)*

The differences in LWP susceptibility between model and observations are discussed, but statistical significance tests (e.g., t-tests, confidence intervals) are not reported. Adding these would strengthen the conclusions.

Thanks for the helpful suggestion. Figure R9 shows the p values for the Welch t-test between Meteosat observations and WRF simulations for each bin. We further marked bins with $p<0.05$ with black outlines as shown in Figure R10. For most MBL clouds, the simulated LWP susceptibilities are significantly different than the satellite observations. For non-precipitating thin clouds, our simulations reproduce the decrease of LWP with weaker magnitude. Yet, the LWP susceptibilities are significantly different from satellite observations for most bins.

To address this comment, we updated Figure 5 and added related discussions in the manuscript. "For non-precipitating thin clouds, the simulated decrease in LWP with increasing aerosol concentration agrees in sign with satellite observations. However, the magnitude of this decrease is weaker, and the simulated susceptibilities remain significantly different from satellite estimates at 95% confidence level for most bins (Figure 5a, c). (Lines 529-533)"

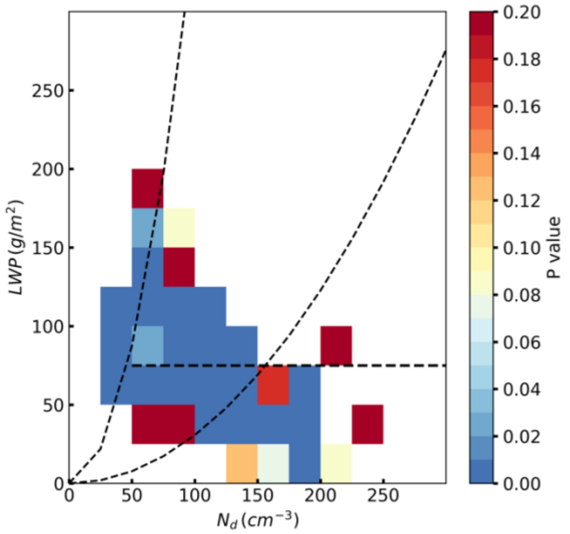

Figure R9 P value for the Welch t-test between Meteosat observations and WRF simulations for each bin.

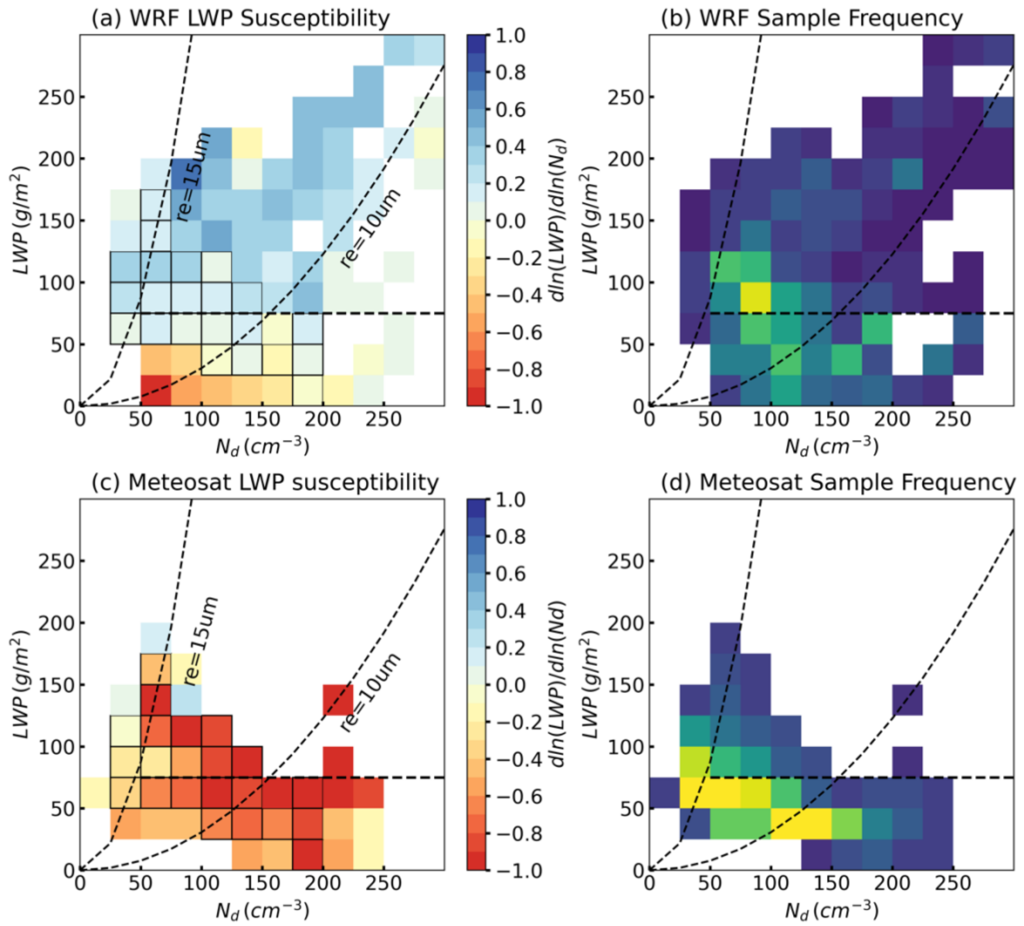

Figure R10. Mean liquid water path (LWP) susceptibility from (a) (b) WRF simulations and (c) (d) Meteosat cloud retrievals during the daytime. (a) (c) cloud LWP susceptibility $dln(LWP)/dln(N_d)$, (b) (d) frequency of occurrence of sample in each bin. The dashed lines indicate r_e =15 μm, r_e =10 μm, and LWP= 75 gm^{-2}, as r_e thresholds for precipitation (precipitating clouds located to the left of the line), and for thick clouds (with LWP > 75 gm^{-2}), respectively. Black-outlined bins denote cases where the WRF and Meteosat LWP susceptibilities differ significantly ($p < 0.05$) based on a Welch's t-test.

- *CFODD Interpretation (Lines 494-523)*

The CFODD analysis is insightful, but the physical interpretation of reflectivity slopes (e.g., why steeper slopes indicate stronger accretion) could be briefly elaborated in the text.

Thanks for the question and suggestion. Based on the definition of droplet collection efficiency (E_c) for a continuous collection model, and the assumption of the relationship between radar reflectivity (Z_e) and cloud drop size, we can derive the relation between Z_e and E_c as

$\frac{dZ_e}{Z_e} \approx \frac{\alpha}{6} E_c d\tau_d$,

where α is a constant and is associated with what variable is conserved in the process, τ_d is in-cloud optical depth. For a complete derivation, please refer to Suzuki et al. (2010) study. Therefore, the slope of the reflectivity changes as a function of τ_d in the CFODD analysis contains information about the droplet collection efficiency E_c. To address this comment, we added the text to the manuscript:

"Based on the relationship between Z_e and the droplet collection efficiency (E_c), the vertical slope of Z_e as a function of in-cloud optical depth (τ_d) is directly linked to E_c, a steeper slope indicates a larger E_c (Suzuki et al., 2010). (Lines 648-650)"

- *Aerosol Prescription (Lines 199-200)*

The assumption of fixed aerosol concentrations (no vertical/horizontal variability) may oversimplify real-world conditions. Acknowledge this limitation and discuss its potential impact on ACI estimates.

Thanks for the suggestion. Yes, the uniform aerosol concentration assumption over-simplifies the spatial and temporal heterogeneity from local emission and long-range transport, the relative location between aerosol plumes and cloud, as well as processes such as wet scavenging, and the reactivation of CCN from evaporated rain drops. In a companion study, we employed the WRF model with the interactive chemistry and aerosol schemes and investigated ACI and its feedback on both clouds and aerosols using same model configuration and cases (but less) as this study (Lee et al., 2025). In Lee et al. (2025), we found a consistent positive LWP response for precipitating clouds as this study (Figure 11 in Lee et al., 2025). As we assumed a higher ratio of the Aitken mode aerosols (80% for the Aitken mode and 20% for the accumulation mode) in that study, and activated CCN and N_d concentrations are much lower in Lee et al. (2025) than in this study. In addition, with the comprehensive aerosol module in WRF-Chem, we found signals of increased reactivation of CCN from evaporated raindrop due to larger aerosols in the accumulation mode.

We added the following discussion to the method section acknowledging the limitation and potential impact: "The fixed aerosol field neglects spatial and temporal variability driven by emissions, long-range transport, wet scavenging, and CCN reactivation from evaporated raindrops. These missing processes can sustain higher CCN concentrations, suppress precipitation, and potentially exaggerate positive LWP responses.

Despite this simplification, our companion WRF-Chem study (Lee et al., 2025) shows that, even with full aerosol microphysics, wet scavenging, and aerosol reactivation, the simulated LWP responses remain broadly consistent with the results presented here, especially the positive susceptibility in precipitating clouds. This agreement suggests that the key findings of this work are robust, although the prescribed-aerosol assumption may still contribute to some of the quantitative discrepancies discussed in Section 3. (Lines 250-260)"

- *Diurnal Cycle (Lines 764-765)*

The model's struggle to capture afternoon cloud dissipation is noted but not explored. A brief discussion of potential causes (e.g., radiation biases, entrainment rates) would be helpful.

We added the discussion on the potential causes for the model missing the diurnal variation in clouds. Please refer to major comment #1 for details.