Review of egusphere-2025-5935

This manuscript examines the susceptibility of marine warm clouds to aerosol loading over the South China Sea (SCS) under contrasting monsoon regimes, using CERES–MODIS cloud retrievals and MERRA-2 aerosol reanalysis. The monsoon period is classified into three phases (SWMW, NEMW, NEMD), and the study investigates how humidity and lower-tropospheric stability modulate ACI. The topic is relevant given the limited observational constraints on ACI over the SCS, and the scientific question of how monsoon-driven environmental contrasts regulate ACI is well motivated and worth pursuing.

While the manuscript is designed in a self-consistent and logical way, I have noticed several concerns, some of which are fundamental, that inevitably compromise the scientific robustness of the results and conclusions. These include the ***N_d* retrieval methodology**, the **ACI metric definition**, the **choice of aerosol proxy**, and the **absence of cloud-regime separation**, each of which introduces systematic biases or confounds that propagate into the core analysis. I am therefore unfortunately unable to recommend publication in its current form, though I would encourage resubmission after carefully considering the main concerns listed below. I recognize that some may be challenging to address in full, but I would appreciate at least the consideration of adopting more robust satellite datasets and a rigorous discussion of the potential uncertainties and limitations.

Main Comments

ACI_{Nd} definition:

The definition of ACI_{Nd} in Eq. (2) appears to be inconsistent with the standard formulation used by the community. As originally defined by Feingold et al. (2001) and subsequently adopted by McComiskey et al. (2009) and McComiskey and Feingold (2012), the N_d susceptibility (ACI_{Nd}) is given by:

$$ACI_{Nd} = d \ln N_d / d \ln \alpha$$

where α is an aerosol proxy (e.g., AOD, AI, or N_{CCN}). The factor of 1/3 actually relates the two ACI metrics to each other through the Twomey relationship: at constant liquid water path, $N_d \propto r_e^{-3}$, so that $ACI_r \approx (1/3) \cdot ACI_{Nd}$. Thus this factor of 1/3 is a theoretical conversion between the two metrics, not a component within the definition of ACI_{Nd} itself.

However, Eq. (2) in the manuscript defines $ACI_{Nd} = d \ln N_d / 3\, d \ln N_{CCN}$, which places the factor of 3 in the denominator of the ACI_{Nd} expression. This formulation would yield ACI_{Nd} values that are systematically one-third of those obtained using the standard definition, thereby underestimating the N_d susceptibility to aerosols. Please clarify whether this is a typo in the equation (with the actual calculations performed correctly using $d \ln N_d / d \ln N_{CCN}$), or whether the factor of 1/3 was indeed applied in the computation. If the latter is the case, all reported ACI_{Nd} values would need to be recalculated, and any quantitative comparison with other studies that use the standard definition would be invalid.

Study period and Aqua orbit drift:

The entire study period (January 2022 to February 2023) coincides with Aqua's free-drift phase. Aqua completed its last orbit-maintenance maneuver in December 2021 and its mean local equatorial crossing time drifted progressively from the nominal 1:30 PM, exceeding the 1:45 PM science upper limit by February 2023. A later crossing time means systematically higher solar zenith angles at observation time, which can bias MODIS cloud optical property retrievals (τ, r_e) and consequently any derived N_d (Twedt et al., 2023). To date, no formal assessment of CERES-MODIS retrieval quality during the drift period has been published. Could the authors clarify why this study period was chosen, or otherwise, put some discussion on whether the drifting observation geometry may introduce systematic biases into the cloud properties?

Satellite N_d derived:

A systematic concern arises from the derivation of cloud droplet number concentration (N_d) using Eq. (3), which is applied to 1° gridded mean cloud properties (τ, r_e) from the CERES–MODIS SSF product. The N_d formula is a strongly nonlinear function of its inputs, scaling as $\tau^{1/2} \cdot r_e^{-5/2}$. Applying this formula to grid-box-averaged τ and r_e, rather than to individual pixel-level retrievals, introduces a systematic bias through Jensen's inequality: because $r_e^{-5/2}$ is a convex function, the mean of $r_e^{-5/2}$ over a population of pixels is always greater than the function evaluated at the mean r_e. The practical consequence is that N_d computed from pre-averaged cloud properties will differ systematically from the true grid-box-mean N_d, which should be obtained by first computing N_d at the native MODIS pixel resolution (~1 km) and then spatially averaging.

Moreover, the $r_e^{-5/2}$ dependence makes this bias particularly severe, because even modest sub-grid variability in r_e is strongly amplified in the resulting N_d. A 1° × 1° ocean grid box may contain on the order of 10^4 MODIS pixels spanning a wide range of cloud optical thickness and droplet size, including mixtures of polluted and clean clouds, thin and thick clouds, and in some cases liquid-phase and ice-phase pixels. Computing N_d from the grid-box mean of such a heterogeneous population is physically inconsistent with the adiabatic cloud assumption that underlies Eq. (3), which is intended to apply to individual, reasonably homogeneous cloud columns. The South China Sea also presents a challenging environment for satellite N_d retrieval, given the prevalence of broken cumulus and congestus clouds where the adiabatic assumption is less reliable than in stratocumulus-dominated regions.

Furthermore, using the 1° gridded product to derive N_d may forfeits the ability to apply pixel-level quality control filters that are essential for reliable N_d estimation. Grosvenor et al. (2018) demonstrated that filtering at the pixel level to remove retrievals affected by high solar zenith angles, broken cloud contamination, optically thin clouds ($\tau < 3$), and anomalously large r_e (indicative of precipitation or multi-layer cloud contamination) is necessary to obtain robust N_d estimates. These filters cannot be meaningfully applied after spatial averaging has already occurred.

The satellite remote sensing community has recognized this issue, and established N_d datasets are constructed by computing N_d at the pixel level before aggregation to coarser grids. I therefore recommend that the authors replace their self-derived N_d with a community-standard product. One option is to compute N_d from the MODIS Level-2 (MYD06/MOD06) pixel-level τ and r_e retrievals (preferably the 3.7 μm channel) with appropriate quality screening applied at the pixel level, following the recommendations of Grosvenor et al. (2018), and then aggregate the pixel-level N_d to 1° × 1° with caution regarding sampling and filtering choices. Alternatively, the authors could consider the gridded dataset of Gryspeerdt et al. (2022): https://catalogue.ceda.ac.uk/uuid/864a46cc65054008857ee5bb772a2a2b/, which provides 1° × 1° daily N_d computed from pixel-level MODIS Collection 6.1 retrievals (from Aqua and Terra) with multiple validated sampling strategies covering the period 2000–2020, and is well suited for studies of aerosol–cloud interactions of this nature.

Therefore, until the N_d calculation and methodology used in this study is evaluated against aircraft in situ measurements over the South China Sea, I would not put much confidence in the ACI_N relationships derived here. I encourage the authors to either conduct a thorough evaluation of their N_d product against available in situ benchmarks, or to adopt a peer-reviewed and widely recognized MODIS N_d retrieval that has already been validated by the satellite remote sensing community.

Cloud regime confounding across monsoon periods

Section 2.6 (lines 200–213) mentions that all liquid-phase warm clouds with CTT > 273 K, CTP between 650 and 950 hPa, $\tau > 5$, and non-raining conditions are chosen. But it appear that no separation by cloud morphological type is applied. The CTP range of 650–950 hPa is fairly broad, encompassing both shallow marine stratocumulus (typically CTP ~ 850–950 hPa) and deeper trade cumulus or congestus (CTP approaching 650 hPa). As a result, the ACI analysis pools fundamentally different cloud populations together within each monsoon period.

This is consequential because the cloud populations differ substantially between periods. During the SWMW, the warm-cloud fraction is only ~40 % (Fig. 6a), indicating that the warm liquid clouds sampled are a small subset of a convectively active cloud field dominated by deep systems. During NEMD, the warm-cloud fraction reaches ~77 % (Fig. 6c), and the subsidence-dominated environment favors extensive shallow stratiform clouds.

Comparing ACIr (or ACINd) across these periods, even after controlling for LWP, very likely not account for the fact that the underlying cloud dynamical context differs drastically: updraft velocities, entrainment rates, boundary layer depths, and cloud lifetimes are all regime-dependent. For instance, a shallow stratocumulus deck under strong subsidence (NEMD) responds to aerosol perturbations may very differently from isolated trade cumuli embedded in a convectively active boundary layer (SWMW), even at the same LWP.

These differences also affect the satellite retrieval interpretation. The 3.7 µm channel r_e retrieval is weighted toward cloud top, but the vertical penetration depth depends on cloud optical depth and the vertical profile of droplet size (Platnick, 2000; Grosvenor et al., 2018). For vertically more uniform stratocumulus, the retrieved r_e approximates the near-cloud-top value reasonably well. However, for cumulus clouds with strong vertical gradients in droplet size and sub-adiabatic profiles due to lateral entrainment, the retrieved r_e is less representative of the actual cloud-top microphysics. Hence, the CER–AI regression slope (ACI_r) may carry different physical meanings across the periods, complicating a direct quantitative comparison.

I suggest that the authors consider separating the analysis by cloud type, or at minimum by CTP sub-ranges that isolate shallow stratiform clouds (e.g., CTP > 800 hPa, corresponding to cloud tops below ~2 km) from deeper cumulus-type clouds. Alternatively, the use of a cloud-regime classification based on joint histograms of τ and CTP (following the ISCCP convention) would enable a more controlled comparison across the three monsoon periods, confining the ACI analysis to a consistent cloud morphological type (e.g., stratocumulus). I would leave that for the authors' consideration.

Aerosol hygroscopic swelling artifact

The MERRA-2 total AOD used to construct AI (Eq. 5) is computed at ambient RH, where the extinction coefficients for sulfate, hydrophilic carbonaceous aerosols, and sea salt are explicit functions of relative humidity (Randles et al., 2017). In humid environments, hygroscopic water uptake inflates AOD (and therefore AI) without a corresponding increase in CCN-active particle number. This creates a spurious flattening of the CER–AI and Nd–AI regression slopes under moist conditions, as the AI axis is stretched by swelling rather than by additional CCN. The three monsoon periods differ substantially in humidity (q ~ 12, 11, and 9.5 g/kg for SWMW, NEMW, and NEMD, respectively), so the progressive strengthening of ACI from SWMW to NEMD (Figs. 8b, 8d) could be partly or wholly an artifact of this systematic humidity difference rather than a physical difference in cloud microphysical sensitivity. The same concern applies to the within-period humidity stratification (Fig. 10): weaker ACI under moist sub-samples may reflect the swelling artifact rather than the condensational growth and coalescence mechanisms proposed (lines 488–508). This confound has been well documented in the ACI literature (Grandey and Stier, 2010; Quaas et al., 2010).

I would suggest the authors consider acknowledging this potential uncertainty and discussing the extent to which the hygroscopic swelling of the aerosol proxy may limit the interpretation of the humidity-dependent ACI results.

ACI-meteorology co-variation

The author finds that ACI strengthens as q decreases and LTS increases from SWMW to NEMD. However, q and LTS are not independent controls. They co-vary tightly with the monsoon phase (Fig. 9 shows this clearly). The within-period stratification (Figs. 10, 11) is a step in the right direction, but the cross-period comparison (which is the headline result) cannot separate the influence of q from LTS from cloud regime from aerosol type and loading, because all of these change simultaneously with the monsoon. The manuscript would benefit from clearly stating this limitation and being more cautious in attributing the cross-period ACI differences to specific mechanisms.

Data collocation: Please specify how the different spatial resolution data are collocated.

Misc. Comments

L162. Here you mentioned AI is used as the aerosol proxy in calculation of ACI, but in the Eq 1) and 2) the CCN is used? Please clarify.

Figure 8. If AI is used as CCN proxy, you can directly state N_d (r_e) vs AI on the Y-axis.

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