Review of “High climatological cloud cover limits its response to aerosols in ICON-HAM” by Jia et al. [MS No., egusphere-2026-569]

This paper examines cloud fraction responses to aerosol perturbations in a climate model, ICON-HAM, with two different cloud fraction parameterizations: one is a relative humidity solely dependent scheme (CC-RH), and another is additionally coupled with cloud water content (CC-RH-LWC). Cloud fraction sensitivities are quantified using an explainable machine learning (ML) framework across three sensitivity runs with different lower-bound Nd values. The authors find that the cloud fraction scheme coupled with LWC has unexpectedly weaker sensitivities than the RH-only scheme, due to the positive feedback of LWC on cloud fraction, which sets a high background cloud fraction and leaves little room for aerosol-induced cloud fraction increase. This state-dependent cloud fraction response is interesting and may help reconcile the discrepancies between the weak cloud fraction responses in current climate models and the strong responses inferred from observations.

The paper is overall well written with very few typos found, and I really like the discussion section that is sound and insightful. That said, the paper may benefit from a slight reorganization of SHAP base values discussions. The current results are primarily based on global samples, despite the inclusion of an exemplary geographical window analysis. I am curious how the results would vary at the reginal scale (see also major comment 1). Some clarification on the ML prediction skill and the rationale for the selected geographical window would also be helpful. After these concerns are addressed, along the with following points, I believe the paper would be suitable for publication in ACP.

Major comments:

1. The paper is primarily based on the global analysis, and I am wondering how the results would vary across different regions. Since a core conclusion is that cloud fraction sensitivities are dependent on background cloud fraction, it would be valuable to examine how the sensitivities change across different low cloud regimes: stratocumulus, transitional clouds, and shallow cumulus regimes. You may refer to the definition of cloud regime by Medeiros & Stevens (2011), which is popularly used in previous studies (e.g., S. Zhang et al., 2016; H. Zhang et al., 2024). Relatedly, please clarify how the exemplary geographical window was selected. Does it represent a specific cloud regime?

2. Clarification of ML models’ prediction skills is needed. Since the SHAP values are based on ML predictions, the ML prediction abilities are important, which may bias the interpretation of cloud fraction sensitivities. For example, H. Zhang et al. (2024) showed that XGBoost skills on predicting low-cloud fraction are lower in updraft regimes compared to downdraft regimes, and therefore the results for subsidence regions may be more trustworthy. Differences in ML prediction skill across the sensitivity runs (Nd,min) may likewise influence the interpretation. Please check the R^2 map for the different runs and discuss how they may influence the sensitivities comparison.

Additionally, please clarify how low-cloud fraction is defined. Is it the maximum cloud fraction below 700 hPa by assuming the max overlapping, or something else? The definition may also influence the current results.

3. The authors argue that due to the head-room effect CC-RH-LWC has unexpectedly weaker sensitivities than CC-RH. One way to reinforce this conclusion would be to compare their cloud fraction sensitivities by controlling for, or sampling, similar background cloud fractions at the same Nd,min to see if CC-RH-LWC then has stronger sensitivities.

4. The authors quantify cloud fraction sensitivities by assuming their linearity over two intervals: [lnNd,min, lnNd,min+0.1] and [lnNd,min+0.1, 6]. This is reasonable for the first interval, since the Nd perturbation is small and the relationships in Figure 3 indeed appear approximately linear. For the interval above lnNd,min+0.1, however, this assumption does not hold, particularly at small Nd,min, as shown in Figures 3d and 3h. Although the influence of computing cloud fraction sensitivities at high Nd on the main conclusion appears minimal, clarifying the limitations of assuming linearity when computing cloud fraction sensitivities over [lnNd,min+0.1, 6] is still helpful.

5. In Section 3.3.2, the authors discuss SHAP base values, which by definition are the mean cloud fractions. It is therefore better to merge this discussion with the description of the mean states of marine low clouds in Section 3.1. Moving it upfront in the paper would provide readers with better background context and also reduce some duplication.

Technical suggestions:

1. Suggest adding the shading (e.g., Q10 to Q90) to the zonal mean lines in Figures 1a-b.
2. Please a description of the numbers shown in each panel in Figure 3.

Minor comments:

L29: Suggest changing “lead” to “leading”

L83: Revise “cloud droplet number concentration” to “Nd”

L101: What is the vertical resolution near the boundary layer? This is important for low cloud simulations.

L102: Please spell out “ECHAM” at first use.

L171: Have you checked the correlations between input features?

L173: What is the contribution of PBLH to the cloud fraction predictions here? I am curious because such diagnostics of PBLH in climate models may not be accurate given their coarse vertical resolutions.

L275: Likely more evident for thin clouds?

L300: For the MODIS analysis, were samples containing middle and high clouds removed? These can contaminate the retrieval of low clouds.

L368: Why does β_b increase from 10 to 40 cm^{-3}, which seems not consistent with observations. Ship-track studies (Yuan et al., 2023) show that cloud fraction sensitivities decrease at higher Nd background.

L398: Revise "Panel (b)" to "Figure 4b".

L480: Please double check the concept of "bottom-up" and "top-down" approaches, which might be used in the opposite sense here. As I understand it, "top-down" seems to refer to the approach of attributing forcing to aerosol perturbations, whereas "bottom-up" refers to estimating forcing from observed cloud sensitivities (e.g., Yuan et al., 2025).

References:

Medeiros, B., & Stevens, B. (2011). Revealing differences in GCM representations of low clouds. *Climate Dynamics*, *36*(1), 385–399. https://doi.org/10.1007/s00382-009-0694-5

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Zhang, H., Zheng, Y., & Li, Z. (2024). Improving low-cloud fraction prediction through machine learning. *Geophysical Research Letters*, *51*(15). https://doi.org/10.1029/2024GL109735

Zhang, S., Wang, M., J. Ghan, S., Ding, A., Wang, H., Zhang, K., et al. (2016). On the characteristics of aerosol indirect effect based on dynamic regimes in global climate models. *Atmospheric Chemistry and Physics*, *16*(5), 2765–2783. https://doi.org/10.5194/acp-16-2765-2016