Response to EGUSPHERE-2024-2559 reviews for RC1

We thank Reviewer #1 for their effort and feedback on our manuscript EGUSPHERE-2024-2559. In response to the suggestions and questions, please find our answers listed below: **Reviewer #1 comments are extracted in bold from original review supplement**; our responses are given directly below in normal font.

The cirrus clouds in the liquid origin regime is formed in lower altitudes, so the aerosol concentration in lower altitudes are also important in determining N_ice in this regime. Therefore, the multiple regression equation might be revised to something as following:

N_ice=beta1a*T(t=0)+beta1b*T(t=-6)+ beta1c*T(t=-12)+ beta2a*w(t=0)+beta2b*w(t=-6)+ beta2c*w(t=-12)+ beta3a*dust(t=0)+beta3b*dust(t=-6)+ beta3c*dust(t=-12)+epsilon,

where t=0 denotes the values at DARDAR observation, t=-6 denotes values 6 hours before, and t=-12 denotes values 12 hours ago (Fig. 2).

This is a valid point, and we considered this carefully during the manuscript preparation. The challenge lies in striking a balance between accurately modeling the dependencies of cloud properties (N_ice / IWC) and maintaining the interpretability of the model.

The small mean standard deviation of dust concentrations along the trajectory, as described in L74ff, supports the assumption that using the dust concentration at t=0 is a reasonable proxy for dust concentrations throughout the trajectory.

[L74ff: *The required input for a linear regression is a single data point, not a time series (e.g., dust along the trajectory). This is why we use the dust particle concentration at the time of cirrus cloud observation (t = 0) as a proxy for the dust concentration along the entire trajectory. The small mean standard deviation of 0.14 log mg kg−1 along the trajectories supports the validity of this simplifying assumption.*]

Reviewer #1’s suggestion of extending the multiple linear regression would indeed provide more input data but would introduce challenges regarding model interpretability due to the strong autocorrelation present in time series data. To account for time series inputs, a more complex model, such as a recurrent neural network (as used by Jeggle et al., 2023), would be necessary. While such models offer improved prediction skill, they come at the cost of reduced interpretability.

Given that the focus of this work is the interpretability of the regression model, we chose a simple linear regression with a small number of input variables. This allows for regression coefficients to be directly linked to physical quantities. Furthermore, by clustering clouds into formation regimes before fitting the regression model, we can effectively disentangle the dust effect from meteorological and regional dependencies.

The paper uses dust with size greater than 1 micron. However, although dusts with size smaller than 1 micron are less effective in acting as INP, it is possible that they

can still play a role. So additional analysis should be performed to demonstrate that these small dust particles are not important for N_ice.

Thank you for this insightful point, which we also considered during the preparation of the manuscript. The decision to exclude dust particles smaller than 1 micron was based on two main reasons. First, as Reviewer #1 noted and as stated in L123, larger dust particles are more efficient ice-nucleating particles (INPs). Second, including submicron dust particles in the linear regression would likely introduce similar issues to those discussed in our previous response, specifically due to the strong autocorrelation in dust concentrations across different size ranges. Therefore, we focused on dust particles larger than 1 micron, which are more relevant to the ice nucleation process in this context.

[L123: . For this study we aggregate the four size bins with radii > 1 μm into a single super-micron size bin. Given that larger particles are more likely to act as INPs (Kanji et al., 2017), we use the super-micron dust bin as proxy for dust particle concentration for this study.]

References

Jeggle, K., D. Neubauer, G. Camps-Valls, and U. Lohmann, 2023: Understanding cirrus clouds using explainable machine learning. Environmental Data Science, 2, e19, https://doi.org/10.1017/eds.2023.14.

Kanji, Z. A., Ladino, L. A., Wex, H., Boose, Y., Burkert-Kohn, M., Cziczo, D. J., and Krämer, M.: Overview of Ice Nucleating Particles, Meteorological Monographs, 58, 1.1–1.33, https://doi.org/10.1175/AMSMONOGRAPHS-D-16-0006.1, 2017.