Reviewer #2:

Comments and Suggestions for Authors:

Major comments:

1. The study's strength lies in its multi-source data approach. However, a more thorough cross-validation and uncertainty quantification between different datasets (e.g., FY-4A, Himawari-8, CDWL) regarding key parameters like cloud phase and height would significantly enhance the robustness of the findings. For instance, beyond noting that FY-4A might misclassify some ice clouds as mixed-phase, quantifying the impact of such discrepancies on the defined life cycle stages would be valuable..

Response: We sincerely appreciate your positive feedback on our multi-source data approach and your highly valuable suggestion regarding cross-validation and uncertainty quantification. We completely agree that quantifying the uncertainties between datasets would significantly enhance the robustness of our findings. However, performing a strict pixel-level or quantitative cross-validation in this specific study is highly constrained by several objective factors:

(1) Spatiotemporal and Geographical Limitations of Himawari-8: The AHI sensor on Himawari-8 relies on visible bands to distinguish clouds and near-infrared bands to differentiate water and ice clouds, meaning its cloud type products are only available during the daytime (with a 10-minute temporal and 5 km spatial resolution). Considering the sunrise time at the study site (valid data available only after 10:00 LT) and observational errors, we have less than 1 hour of valid Himawari-8 data during the non-decomposed ice cloud phase (as shown in Fig. 5a). More importantly, the observation range of Himawari-8 is 60°S-60°N, 80°E-160°W. Our study site (37.06 °N, 82.69 °E) is located at the extreme outer edge of this detection region. Consequently, the cloud type parameter at the study site is frequently a null value, making phase identification heavily dependent on neighboring pixels.

(2) Observational Scale Discrepancies: FY-4A's AGRI sensor covers the entire study region with a 5-minute temporal and 4 km spatial resolution. Conversely, the CDWL utilizes a VAD scanning mode, which acts as a localized, single-point vertical observation. There is a significant scale discrepancy between the satellite's macroscopic grid and the lidar's localized point data.

(3) Inherent Algorithm Uncertainties: As pointed out by Lai et al. (2019), who used MODIS data as a benchmark to compare cloud property classifications between FY-4A and Himawari-8, the overall hit rates for cloud pixels by AHI and AGRI are 77% and 93%, respectively. For ice clouds, the recognition rates are comparable (80% for AHI and 81% for AGRI). However, AGRI's false hit rate for mixed-phase clouds increases to 75%, primarily because pixels classified as mixed-phase by MODIS algorithms are often interpreted as water or ice clouds by AGRI algorithms.

Regarding your perceptive question on how these discrepancies impact our defined life cycle stages, we acknowledge that relying solely on FY-4A might cause temporal shifts when defining the transition from Stage 3 to Stage 4 due to the aforementioned misclassifications. To mitigate this, our stage definition does *not* rely on a single satellite's phase classification. Instead, we use the high-resolution vertical probing of the CDWL (e.g., the descent of cloud base height and the dynamic characteristics of sinking ice virga) as the primary criteria for dividing the life cycle stages. Satellite data serve as a macroscopic evolutionary background to complement the radar data.

Change: Line 123-127. It is worth noting that the study site is located at the extreme western edge of the Himawari-8 detection range (80°E), and its cloud phase product relies on visible and near-infrared bands, resulting in sparse valid daytime data for the target ice cloud. Therefore, rather than absolute pixel-to-pixel validation, this study utilizes the temporal evolution trends and neighborhood spatial consensus from these multi-source datasets to comprehensively complement the CDWL point observations and define the ice cloud life cycle.

Reference:

Lai, R., Teng, S., Yi, B., Letu, H., Min, M., Tang, S., and Liu, C.: Comparison of Cloud Properties from Himawari-8 and FengYun-4A Geostationary Satellite Radiometers with MODIS Cloud Retrievals, Remote Sensing, 11, 1703, https://doi.org/10.3390/RS11141703, 2019.

2. While the paper provides a clear phenomenological description of the ice crystal cloud lifecycle, the discussion on the underlying physical mechanisms could be deepened. A more detailed analysis of processes such as the specific activation mechanisms of dust aerosols as ice nuclei and how turbulence precisely facilitates aerosol-supercooled water interaction, potentially supported by existing theories or model simulations, would strengthen the paper's scientific contribution.

Response: We fully agree that deepening the discussion on the underlying physical mechanisms significantly strengthens the scientific contribution of the paper.

In actual operation, we are faced with the constraint of extreme data volume. Due to the huge differences in the design, focus, and spatio-temporal resolution of multi-source observation instruments, the CDWL observation data volume of the complete ice cloud evolution process captured in this study is very small (less than 2 days). In contrast, other matching reanalysis datasets (such as ERA5, MERRA-2) have lower temporal resolution and fewer samples. This lack of data makes it very difficult to carry out direct statistical correlation discussions, and it also makes conventional numerical model simulations invalid due to the lack of sufficient initial values, boundary conditions, and verification data.

However, your suggestion pointed out the direction of breakthrough for us. We are currently using a 2-year long-term CDWL observation dataset, supplemented by deep learning methods, to systematically tackle this problem. We are introducing generative reconstruction techniques based on Denoising Diffusion Probabilistic Models (DDPM) and Denoising Diffusion Implicit Models (DDIM). We are combining ConvNeXt for large-receptive-field feature extraction and U-Net to solve the ill-posed inverse problem of ice crystal cloud image reconstruction caused by VAD scanning. We use a cross-attention mechanism to guide the high-precision reconstruction using local meteorological parameters, MERRA-2 dust data, and CDWL dynamic parameters to achieve end-to-end inversion from aerosol to ice cloud physical parameters.

To address your immediate concern in this phenomenological study, we have expanded our qualitative discussion in Section 3.2 based on classical theory to explicitly describe the deposition/immersion nucleation mechanisms of dust and the role of turbulence in enhancing collision-coalescence rates.

Change: Line 198-201. Physically, desert dust aerosols trigger glaciation via deposition or immersion freezing at -10 °C to -17.5 °C. The upward transport of these IN is strongly influenced by the PBLH (Holtslag and Boville, 1993). Within this layer, turbulent kinetic energy lifts the dust and generates micro-scale eddies, which accelerate the phase transition by enhancing dust-droplet collisions and local supersaturation.

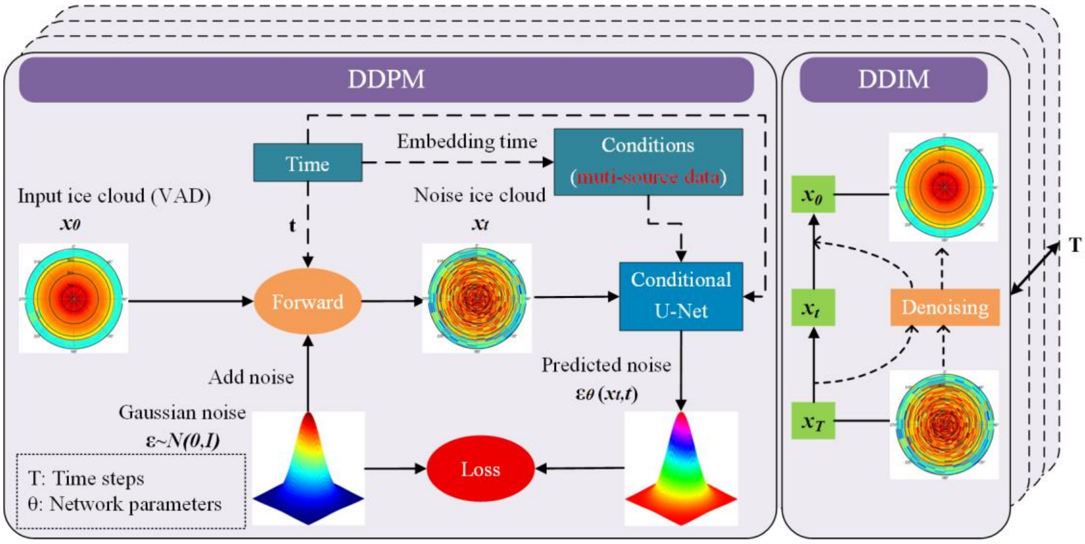

Figure 1. The DDPM+DDIM framework models cross-modal global dependencies between meteorological parameters and ice clouds, where DDPM handles model training and DDIM accelerates inference.

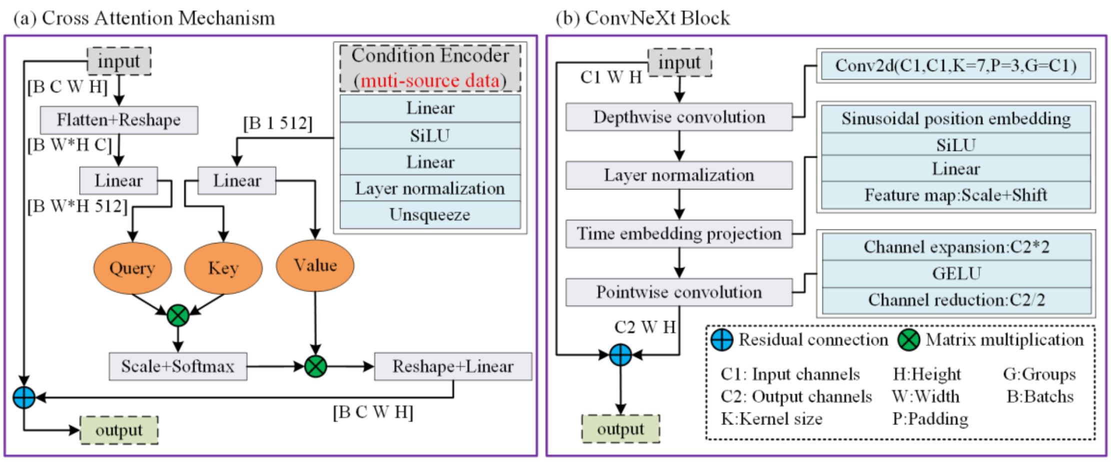

Figure 2. The Cross-Attention mechanism and ConvNeXt module. Cross-Attention captures cross-modal global dependencies between multi-source data and ice clouds; ConvNeXt enables large-receptive-field feature extraction to boost non-linear representation and generalization.