I would like to express my gratitude for your time to review my manuscript and for providing valuable feedback. I understand the considerations and concerns that have led to this conclusion, and I will revise the paper following your comments. Please find below a brief response to the major issues you have highlighted.

1. CNN is not explained in the text.

Reply: Thank you for your suggestion. Below is a more detailed introduction, and more information will be added to my manuscript:

The TIR-CNN model is trained with solar-independent variables (thermal infrared radiances, viewing zenith angles, and altitude) as inputs and uses standard MYD06 products (solar-dependent retrievals in the daytime) as targets. Through training, the model can capture context and learn the complex nonlinear relationship between the input variables and targets, which can be applied in the cloud property retrievals during both daytime and nighttime. The convolutions in the TIR-CNN model are beneficial in considering the information from neighbor fields in training and naturally imputing the missing predictions that failed in the split-window method. Spatial distributions, optical and microphysical properties of clouds are all determined by the meteorological backgrounds, so cloud properties are statistically connected to the horizontal distribution of clouds. On the other hand, the cloud pixels are not independent at the horizontal scale due to net horizontal radiative transports, especially for high-resolution satellite data. Therefore, a CNN-based deep learning architecture is able to capture the statistical features among adjacent pixels of satellite observations as a robust solution for retrieving cloud optical and micro-physical properties.

Furthermore, the following two independent papers also show the benefits of deep learning in the infrared retrieval of cloud optical thickness:

[1] Tana, et al. 2023: Retrieval of cloud microphysical properties from Himawari-8/AHI infrared channels and its application in surface shortwave downward radiation estimation in the sun glint region, Remote Sens Environ, 290, https://doi.org/10.1016/j.rse.2023.113548, 2023.

[2] Z. Zhao et al., “Cloud Identification and Properties Retrieval of the Fengyun-4A Satellite Using a ResUnet Model,” IEEE Transactions on Geoscience and Remote Sensing, vol. 61, pp. 1–18, 2023, doi: 10.1109/TGRS.2023.3252023.

2. Eqs. (3) and (4) do not correspond to each other.

Reply: Thank you for your meticulous review.

I found a mistake with the introduction after reading your comment. I used Eq. 4 in an early version of code for iterations, and switched to a gradient descent method later. Recently I am using Eq. 4 for another on-going work, and I forgot that I switched to a new method in this paper when I wrote the draft. I am sorry for inconveniences induced by the mistake.

I revised the description of the iteration method that was finally used in the code, and attached two figures showing the change of cost functions in the training process:

The gradient descent is used to minimize the cost function in Eq. (3) in the iteration process,

$$X_{i+1} = X_i - \theta \frac{\partial J_{i,n}}{\partial X_{i,n}}, \tag{5}$$

where

$$\frac{\partial J_{i,n}}{\partial X_{i,n}} = \frac{J(X_{i,n}+\delta x_n)-J(X_{i,n})}{\delta x_n}, \tag{6}$$

and θ represents a learning rate and n represents the n-th cloud parameters (COT, CER and CTH), δx_n represent the small increase in n cloud parameters and $J(X_{i,n} + \delta x_n)$ are calculated using LUTs.

To illustrate the changes in cost with each iteration, I have included the following graphs.

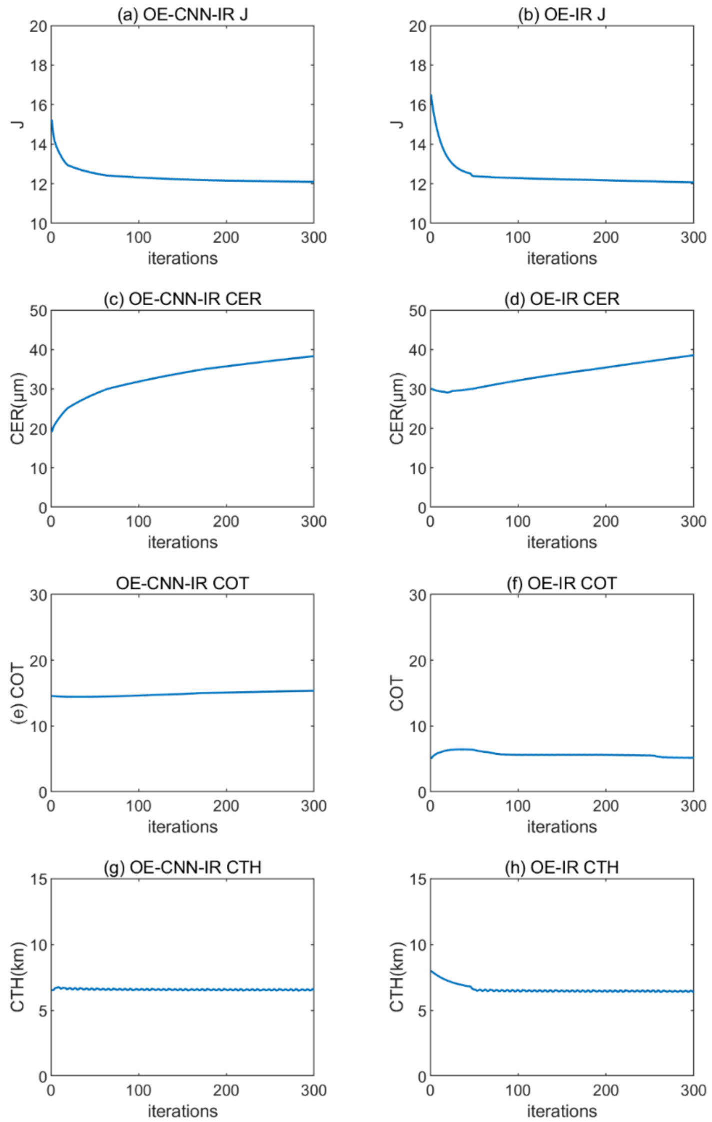

Figure 1. The change of cost function (upper row) and cloud parameters (lower three rows) in the iteration processes, for an illustrative ice cloud layer with large optical thickness. Left pictures are results for OE-CNN-IR method, right pictures are for OE-

IR method.

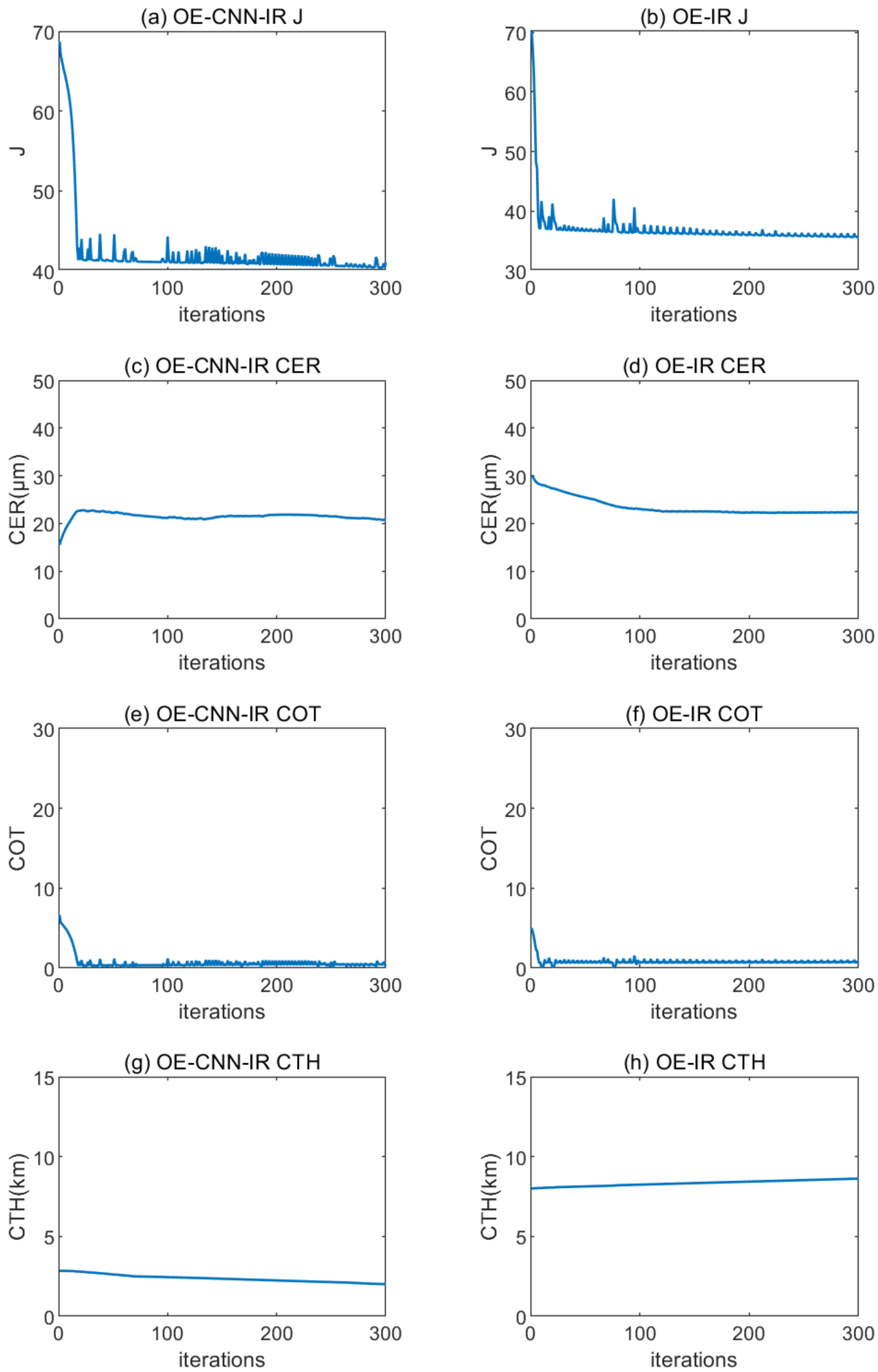

Figure 2. The change of cost function (upper row) and cloud parameters (lower three

rows) in the iteration processes, for an illustrative ice cloud layer with small optical thickness. Left pictures are results for OE-CNN-IR method, right pictures are for OE-IR method.

3. The test retrievals and analysis of the retrieval results

Reply: To better illustrate the improvement, I added panels with probability density. The probability density functions in (Fig. 3) reveals that the OE-CNN-IR retrievals contains a lot of cases with COT>15, which is consistent with MODIS, but OE-IR retrievals do not contain clouds with COT>15, consistent to Wang et al. 2015. As we know, thick clouds do exist, so the OE-CNN-IR significantly outperforms the traditional OE-IR in simulating the COT of thick clouds.

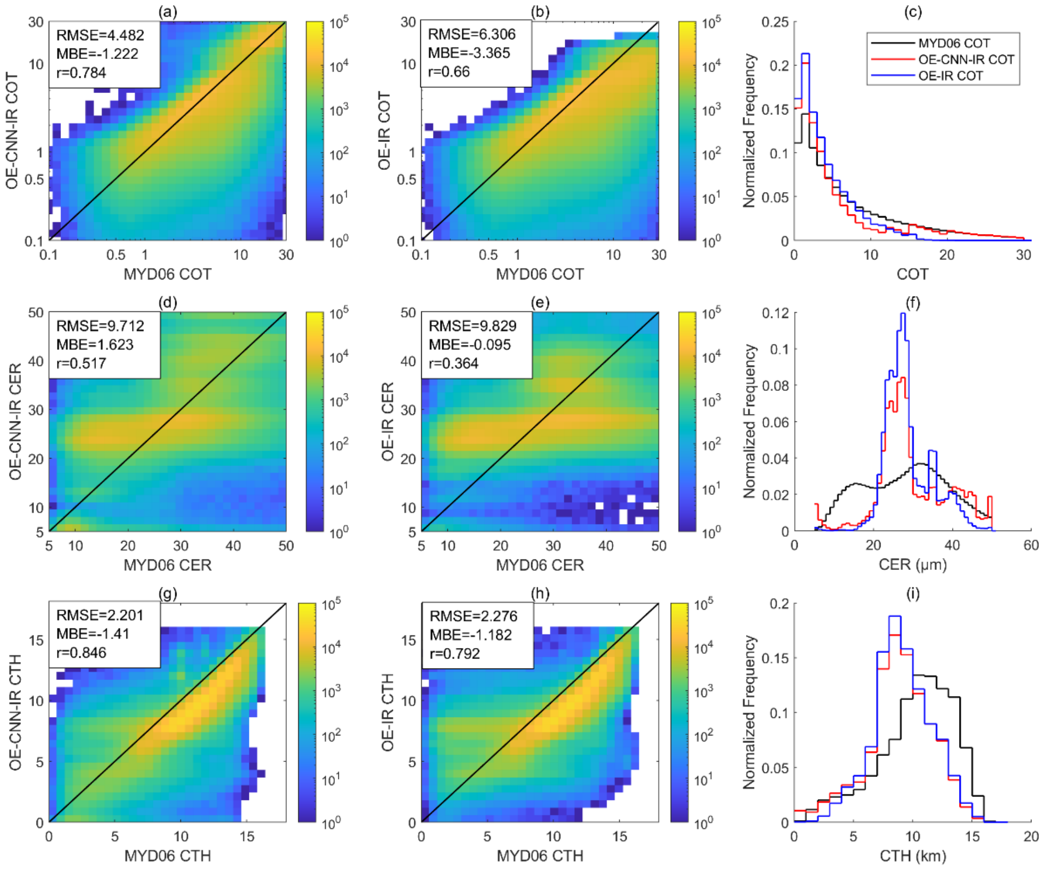

Figure 3. Scatterplots of the pixel level comparisons between the retrievals and MYD06 products for ice clouds over oceans. (left column) Pixel-by-pixel comparisons of COT, CER, and CTH from OE-CNN-IR with the MYD06 ice cloud products over ocean in 2009. (middle column) Scatterplots of the pixel level comparisons between the MYD06 cloud products and OE-IR comparable retrievals. (right column) The probability density functions obtained from MYD06 products, OE-CNN-IR and OE-IR derived results are presented. Color shadings denote the number of observations in each respective pixel. All comparable retrievals are constrained to cases with SZA < 60° and latitude between 60°S and 60°N.

Your insights and comments are greatly appreciated and have offered me a clearer direction on how to improve my research and manuscript. Moving forward, I am committed to addressing the issues highlighted in my feedback and refining my work. I believe that with further development and research, the manuscript will be significantly improved.

Once again, thank you for your time, expertise, and constructive criticism. I am looking forward to your further comments.