Response to Reviewer # 2

We thank the reviewer for his review and valuable comments. The manuscript has been modified according to the suggestions proposed by the reviewer. The remainder is devoted to the specific response item-by-item of the reviewer's comments.

RC=Reviewer Comments

AR=Author response

TC=Text Changes

General comments:

This study proposed a cloud properties retrieval algorithm combining the optimal estimation (OE) method and convolutional neural network (CNN) method based on the infrared (IR) bands, in which the CNN-IR provides the a priori information of COT, CER, and CTH. Results indicate that the OE-CNN-IR method generally performs better than the stand-alone OE method (i.e., OE-IR) with fixed a priori values. In addition, OE-CNN-IR can retrieve all-day cloud properties that traditional two-channel methods using VIS and SWIR bands fail. The main concerns need to be addressed before accepting the manuscript.

Reply: We thank the reviewer for the valuable comments and suggestions. The paper has been improved after addressing all the comments.

1.In terms of methodology, the authors need to be more specific about what improvements OE-CNN-IR has and the motivation for the combination of OE and CNN, in comparison to the TIR-CNN method, as the OE-CNN-IR iterative process is highly dependent on the priori information that TIR-CNN provides. Particularly, the cloud properties derived by TIR-CNN seem to have higher consistencies with those of MYD06 than OE-CNN-IR in Fig. 6.

Reply: Thank you for your suggestions and we have revised 2.2 as follows (Lines 139-155):

The core algorithm of our inversion method is the optimal estimation method, which utilizes the CRTM as the forward model and incorporates CNN results as a prior information. Figure 1 illustrates the architecture of our retrieval models. Initially, temperature, humidity and ozone from the Fifth Generation of the European Centre for Medium-Range Weather Forecasts (ECMWF) Reanalysis (ERA5) (Hersbach et al., 2020) are used to construct lookup tables for each 0.25°x0.25° spatial grid box. These LUTs enumerate the BT for each channel corresponding to varying COT, CTH and CER. Subsequently, the OE method is performed to retrieve cloud properties. The OE method can get the optimal solution by accounting for all spectral information. However, the iteration may have started a long way from the solution in nonlinear problem and the cost function decrease is much slower. Start with a better first guess rather than climatology value can make the process converges much more quickly (Rodgers, 2000). The deep learning methods can achieve high accuracy, and once trained, they offer very fast prediction speeds. However, due to multiple neural networks, deep learning results often lack interpretability, leading to the perception of deep learning as a black box model. In OE-CNN-IR approach, the TIR-CNN derived cloud properties provide a priori state for iterative processes, which is subsequently refined through iterative minimization of the objective cost function, while the climatology values were used as starting points in OE-IR. This method iteratively adjusts parameters to reconcile radiative transfer simulations with observed data. Further details are presented below.

2.P3L83, please clarify the main purpose of this study instead of 'A great number of cloud property users favor remote sensing products that offer explicit physical interpretations', which is too arbitrary. In my opinion, one of the biggest advantages of OE compared with CNN is that it could provide retrieval uncertainty, while CNN fails. In this case, any information on the retrieval uncertainty might be more valuable.

Reply: Thanks for the suggestion. We mean that deep learning models, especially neural networks, consist of numerous layers and parameters (weights and biases). The interactions between these layers can be intricate, making it difficult to trace how input data is transformed into output predictions. Unlike traditional models, where parameters can be directly interpreted (like coefficients in linear regression), deep learning models do not provide straightforward explanations for their outputs, and this is the primary criticize on deep learning models in discussions. It is worth noting that CNN model is able to provide an uncertainty interval on retrievals using the bootstrapping method.

3.In addition, the authors should have provided more explanation and physical meaning on the OE-CNN-IR. To emphasize the advantage of OE, I encourage the authors to extend the study of Fig. 4 using the synthetic data, by conducting information content analysis to check the best combination of available wavelengths, investigating the effects of values of Sy, Sa and Xa on the retrieval, error component analysis, etc.

Reply: Thank you for suggestions and more detailed description have been added in chapter 2.2 as follows (Lines 151-154):

In OE-CNN-IR approach, the TIR-CNN derived cloud properties provide a priori state for iterative processes, which is subsequently refined through iterative minimization of the objective cost function, while the climatology values were used as starting points in OE-IR.

For the chosen of channels, we added the following statement (Lines 106-108):

All channels with wavelength greater than 6.5μm are used, except that the 30th channel (primarily used for ozone retrievals) is not used to reduce uncertainties induced by ozone.

4.Table 1, the detailed wavelength information should be provided, in addition, why is the solar zenith angle excluded in the algorithm? What is the meaning of 'cloud phase infrared', 'cloud phase optical properties'?

Reply: The detailed wavelength information has been added. Solar zenith angle was limited less than 60° for comparison and I have added this parameter in table 1. More detailed information has been added as follows (Lines 110-114):

The product in Table 1, reported in Cloud Phase Optical Properties is the daytime-only phase used in the MYD06 cloud optical retrievals and Cloud Phase Infrared is a daytime and nighttime product derived from three IR window channel pairs. Cloud Phase Optical Properties is used in daytime to determine cloud types while Cloud Phase Infrared is used in nighttime only in our paper.

5.In Figure 1, the flowchart is relatively simple, and some details of the inversion are still unclear, e.g., what is the priori information, is there any cloud phase detection, etc.?

Reply: Thank you for your suggestions and more detailed description has been added in 2.2 as mentioned in General comment 1.

The sensitivity analysis in Figure 2 shows that when the COT is larger than 10, the changes of BT caused by the COT are no longer obvious, are the retrieval results reliable in the larger COT conditions?

Reply: When COT exceeds 10, the infrared radiances are no longer sensitive to COT, so the inversion results primarily depend on the TIR-CNN outputs, which have good agreements with the MODIS results (Wang et al. 2022), so the retrievals are still good, though less accurate than thinner clouds.

Fig.5 is a little bit confusing, since the authors want to emphasize the advantage of OE-CNN-IR, while the simulated BT based on the OE-CNN are more consistent with the observation than those of OE-CNN-IR. Then the readers might understand that OE-IR can get a more accurate retrieval through a better fitting of the observed spectral. In this case, I suggest authors provide more information on the retrieval, such as the degree of freedom.

Reply: Thanks for the suggestion. Here, we present a comparison between the simulated brightness temperatures from CRTM under different cloud property inputs and the observed values. The results adjusted by OE show improved performance over those obtained from the TIR-CNN. The OE-IR BT (brightness temperature) results are slightly better than those of OE-CNN-IR BT. This is primarily because OE-CNN-IR relies on the results from TIR-CNN for its iterations, and since Sa has a significant weight in the cost function, the weight of (y - F(X)) is reduced, while Sa can be ignored in OE-IR. As a result, the comparison between the converged simulated brightness temperatures and the observations is slightly less favorable.

More detailed information has been added in 2.2.3 (Lines 251-252):

When the uncertainties of a priori state are large (e. g., OE-IR), the cost function J is primarily influenced by the first term in OE-IR. If the uncertainties of a priori state are small, then the second term is also important in the iteration process (e. g., OE-CNN-IR).

P11L227, iterations over 200 times seem to be meaningless since the cost function has converged after several times iterations according to Fig.4. In addition, there is no information on the 'real' COT, CER, and CTH in Fig. 4.

Reply: We added MYD06 values as reference in Fig.4 as suggested.

Section 2.1.2, the title of "Active Lidar Detection cloud products" is misleading as the DARDAR product is based on CALIOP and CPR observations.

Reply: Thank you for pointing our issues and the title has been revised as 'Lidar-radar Detection cloud products'.