Report 4

Reply to Anonymous Referee #5

This study develops a numerical inversion algorithm to simultaneously retrieve AOD, SSA, and land surface reflectance using multi-angle polarimetric data from the Gaofen-5 DPC. By employing an optimization-based approach and validating against both simulated data and AERONET observations, the authors demonstrate the potential of DPC for global aerosol monitoring. While the topic is relevant and the retrieval framework shows promise, significant concerns remain regarding the methodology's novelty, the representativeness of the simulated data, and the rigor of the validation process. My specific comments are as follows:

The authors appreciate the reviewer for the constructive comments and thoughtful suggestions, which are very helpful in improving our manuscript. We have carefully considered all the comments and revised the manuscript accordingly. Below is a detailed point-by-point response to these comments.

1. The English expression should be refined to meet academic writing standards.

We thank the reviewer for this comment. We have revised the manuscript and improved the expression.

2. Lines 54-56: please clearly justify what novel contribution this work makes beyond RemoTAP, GRASP, and ML-based approaches.

We thank the reviewer for this important comment. The novelty of this work does not lie in proposing a new inversion theory, but in extending a physically based inversion framework to enable global-scale SSA retrieval from DPC observations, which has not yet been comprehensively demonstrated. While global DPC AOD products already exist, applications of GRASP- or RemoTAP-type methods to DPC-based SSA retrieval have so far been limited to regional studies. In addition, GRASP and RemoTAP typically retrieve aerosol microphysical parameters as intermediate variables, while this study directly retrieves commonly used optical properties (AOD and SSA) within the same physical inversion framework. This represents an alternative implementation strategy rather than a fundamental methodological difference.

Regarding ML-based approaches, although they have demonstrated strong performance, they rely on representative training datasets, and their performance may decrease in regions or conditions with limited observations. For example, Dong et al. (2024) reported anomalously high AOD values over South America in October 2019, whereas both our results and the MODIS AOD show relatively low values in that region. The physically based framework adopted here does not depend on training samples and is therefore better suited for consistent global-scale applications.

We have also revised the manuscript in L55-59 to clarify these points:

> *Moreover, although machine learning approaches have demonstrated strong performance, they are typically data-driven and rely on the availability of representative training samples, without explicitly modeling the underlying physical mechanisms. As a result, their performance may decrease in regions or conditions with limited observations. On the other hand, studies applying physically based inversion methods to DPC observations for global SSA retrieval are still relatively limited. Further efforts are therefore needed to extend such physically based approaches on the global scale.*

3. Section 2.8: there is no evidence that the simulated data realistically represent actual DPC observations, and the manuscript fails to quantify potential biases arising from the integration of multiple data sources.

Thank you for the comment. In Sect. 2.8, the simulated measurements were designed to be consistent with DPC observations in both geometry and uncertainty. Specifically, we added Gaussian noise to the simulations using the DPC laboratory calibration uncertainties, i.e., an error of 5% scalar reflectance and an error of 0.02 for DOLP. The retrieval experiment using simulated data is motivated by the fact that the actual on-orbit observation errors are difficult to quantify. Therefore, we use a simulated dataset with controlled errors to evaluate retrieval performance under well-defined measurement uncertainties.

The observation geometry used in the simulations (including SZA, VZA, and RAA) was taken from the corresponding DPC measurements, so the angular sampling matches real DPC viewing conditions. The DPC observations were also matched with AERONET aerosol products and MODIS surface data to better reflect actual atmospheric and surface conditions at the time and location of the DPC overpass.

Regarding potential biases from integrating multiple data sources, we emphasize that our retrieval experiment is conducted on simulated observations with controlled measurement errors, and the retrieval results can be compared directly with the known "true" inputs used in the forward simulations. This avoids additional ambiguity from errors in validation data, and provides a clear baseline for diagnosing algorithm performance.

4. Lines 157-159: how the multi-angle information from DPC is utilized in the proposed retrieval method?

We thank the reviewer for this comment. Measurements of scalar reflectance and DOLP from multiple viewing angles are jointly used in the inversion, together constructing the measurement vector. These multi-angle measurements are simultaneously fitted within a unified inversion scheme through a least-squares optimization. The multi-angle observations are particularly important for constraining angular dependence of surface reflectance, which helps reduce the coupling between surface and atmospheric contributions and improves the stability of the retrieval. The usage of multi-angle measurements have been added to the revised manuscript in L167-174:

> *The measurement vector, $\boldsymbol{y}$, is constructed with calibrated scalar reflectance at 443, 490, 565, and 670, as well as DOLP at 490 and 670 nm from several angles… Consequently, the scalar reflectance and DOLP at each wavelength consist of measurements acquired from 9 viewing angles.*

5. Lines 200-202: it is unclear whether the actual DPC observation scattering angle distribution has been considered.

We thank the reviewer for pointing out this missing information. The actual DPC observation geometry was considered in the simulations. The SZA, VZA, and RAA used in the simulations were taken from the matched DPC observations, thereby accounting for the actual scattering angle distribution of DPC observations. We have added this information in the manuscript in L223-227:

> *The simulated dataset was constructed using aerosol parameters derived from daily AERONET observations selected within an 8 km radius of DPC overpass locations to represent typical aerosol conditions observed by DPC. The corresponding viewing geometry, including SZA, VZA, and RAA, was taken from the matched DPC observations and used in the radiative simulations, thereby accounting for the actual scattering angle distribution of DPC observations.*

6. Section 3.1: the authors should clarify its relevance to the study.

Thank you for this comment. Sect. 3.1 is included to explain the practical difficulty of retrieving SSA from DPC-like measurements. The sensitivity experiment quantifies the changes in I and DOLP induced by small SSA perturbations, and shows that in many situations these changes are comparable to, or smaller than, the current measurement accuracy. This directly helps interpret why SSA retrievals often have relatively large uncertainties in existing products, and it also provides a quantitative reference for the observation accuracy required to improve SSA retrieval performance in future instruments.

7. Figure 5: the same AERONET-MODIS matched dataset both to generate the simulated observations and to validate the retrievals? Please clearly clarify this point.

We are sorry for the confusion. The AERONET-MODIS matched dataset is used as the reference atmospheric and surface parameters (refered as the "true values" in the manuscript) to simulate the TOA radiance that would be received by the DPC instrument through a forward radiative transfer model. These simulated radiances are then taken as input to the retrieval algorithm, and the retrieved results are finally compared with the same reference dataset ("true values") to evaluate the retrieval performance. Therefore, the matched AERONET-MODIS dataset serves as the physical "truth" for a controlled retrieval experiment, which is a common approach to assess algorithmic performance under idealized conditions.

8. Figure 7: The validation accuracy against AERONET is markedly lower than that obtained with simulated data; how do the authors justify the reliability of the simulation-based validation? Are the AERONET datasets used for simulation-based and real-observation validation independent, or is there potential overlap that could bias the results?

We thank the reviewer for this comment. The higher accuracy in the simulation-based validation is expected and does not imply that the same performance can be achieved for real DPC observations. The simulation experiment is a controlled retrieval test (the construction workflow of simulated dataset has been clarified in our response to the previous comment and in the revised manuscript), and its better performance mainly comes from: (1) controllable observation errors in the simulated TOA radiances, whereas real DPC measurements may have larger uncertainties which have not yet been well quantified (e.g., DPC DOLP uncertainty may exceed 0.04; scalar reflectance calibration reduces systematic biases but random errors remain); (2) comparison against a prescribed "truth" without additional measurement uncertainty, while real-observation validation against AERONET inevitably includes uncertainty in the reference itself (e.g., AERONET SSA uncertainty is ~0.03); and (3) a more consistent forward-inverse modeling setting, which reduces model-mismatch effects compared with real observations (this factor is likely secondary). We have revised the manuscript in Sect. 3.3 to state these points more clearly, and to avoid potential misunderstanding about the relationship between the simulation-based evaluation and the real-observation validation:

9. Lines 318-320: this explanation is not convincing, as such pronounced striping is not evident in the corresponding true-color imagery.

We thank the reviewer for this helpful comment. The true-color image used for comparison is from MODIS and VIIRS, which provide single-view scalar observations with smoothly varying viewing geometry. In contrast, DPC uses multi-angle polarimetric measurements, and viewing-angle discontinuities can occur between adjacent scans. When the satellite switches from one cross-track scan to the next, the distribution of viewing angles changes sharply. Moreover, due to aging of the DPC optical components, the radiometric response experienced VZA-dependent drift. Therefore, the magnitude of radiometric drift may differ between adjacent scans. Although radiometric calibration is applied before the retrieval process, this correction cannot completely remove the VZA-dependent residual errors. These residual differences may lead to meridional discontinuities in the retrieval results.

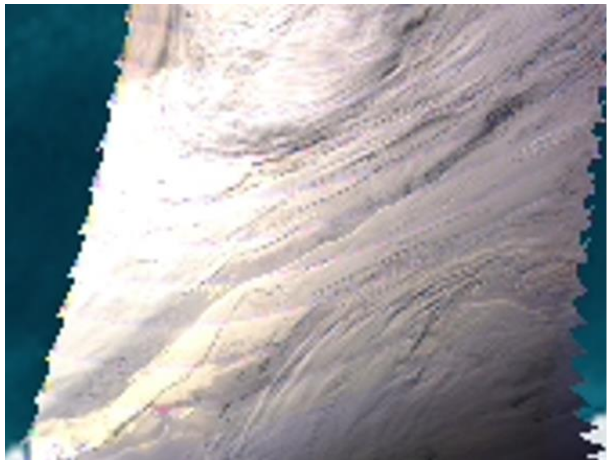

Fig. R4-1. An example of true-color image from DPC observation.

We further examined DPC true-color imagery for verification. Because the resolution of DPC true-color imagery is lower, and over bright desert surfaces the striping is less visible due to limited contrast. In comparison, over more uniform backgrounds with better contrast, such as vegetated areas or scenes dominated by optically thick clouds, the striping pattern is much easier to identify.

We have revised the manuscript and added a more detailed discussion in L389-396:

> *The meridional discontinuities in Fig. 9(b,c) primarily originate from abrupt changes in the observed radiance between successive cross-track scans of DPC, rather than from the retrieval algorithm itself. These discontinuities arise when the instrument switches from one cross-track scan to the next, during which the distribution of viewing angle changes. Due to aging of the DPC optical components, the radiometric response exhibits VZA-dependent drifts. Consequently, variations in viewing-angle distribution lead to variations in the magnitude of this drift, leading to radiance inconsistencies between adjacent scans. Although radiometric calibration is applied prior to the retrieval, the VZA-dependent residual errors*

cannot be completely eliminated. These residual radiometric differences ultimately result in the meridional striping patterns seen in the retrieval results.

10. Figure 10: The cloud masking appears to be problematic, resulting in extensive missing retrievals and apparent errors in the global 440 nm AOD product.

We thank the reviewer for this important comment. We agree that the cloud screening in the previous version was not sufficiently robust in some regions. We found that some abnormal retrievals are mainly caused by residual cloud contamination, such as the anomalously high AOD at high latitudes in Fig. 10(c,d), and the abnormally low SSA values over South America in Fig. 11(b) and over northern Asia in Fig. 11(c). The extensive areas with missing retrievals are primarily due to persistent cloud cover in that month, and partly to the removal of otherwise clear pixels during cloud masking.

In the revised manuscript, we have implemented a more rigorous cloud screening procedure to mitigate these issues. To reduce the risk of retaining cloudy pixels, we adopted more conservative thresholds. For example, given that the uncertainty at 865 nm can be as large as ~23%, we increased the screening threshold by 20%. Over land, the criterion (R_{865}/R_{443}) was adjusted from 1.2 to 1.44. Over ocean, the threshold was adjusted from 0.40 to 0.32. This tightening is intended to maintain robust cloud removal even when the uncalibrated 865 nm reflectance is positively biased. Following this update, the artifacts mentioned above are substantially reduced, and the global patterns exhibit improved spatial consistency. Nevertheless, the stricter screening inevitably excludes more valid clear-sky pixels, resulting in reduced spatial coverage. It is difficult to simultaneously maintain broad data coverage and completely eliminate cloud contamination. In the revised version, greater emphasis is placed on more rigorous cloud screening to ensure reliable retrieval results, which inevitably leads to reduced spatial coverage.

Reference

Dong, Y., Li, J., Zhang, Z., Zheng, Y., Zhang, C., & Li, Z. (2024). Machine learning-based retrieval of aerosol and surface properties over land from the gaofen-5 directional polarimetric camera measurements. *IEEE Transactions on Geoscience and Remote Sensing*, *62*, 1–15. https://doi.org/10.1109/tgrs.2024.3419169

Zheng, F., Hou, W., & Li, Z. (2019). Optimal estimation retrieval for directional polarimetric camera onboard chinese gaofen-5 satellite: An analysis on multi-angle dependence and a posteriori error. *Acta Physica Sinica*, *68*(4), 040701. https://doi.org/10.7498/aps.68.20181682