Review of ACP egusphere-2026-5788 manuscript Global Hourly Aerosol Optical Depth Retrieval from DSCOVR/EPIC Observation and Its Application in Extreme Wildfire Events by Sun et al

Summary

This manuscript, submitted for publication in ACP, describes a machine learning (ML) application to derive spectral aerosol optical depth (AOD) over land for multiple fire events. The authors make use of a ML tool referred to as the Deep Learning (DL) package that ingests radiance measurements at 10 wavelengths by the Earth Polychromatic Imaging Camera (EPIC) in the Deep Space Climate Observatory (DSCOVR) stationed at the Lagrangian 1 (L1) point. An analysis of the DL retrieval tool performance, in relation to those of standard EPIC MAIA and UV algorithms, is carried out by inter-comparing the levels of agreement of these three retrieval approaches with AERONET observations at 500 nm. The reported results are of great interest. As currently written, however, the article portraits the DL-retrieval tool as a black-box that internally infers the outcome of the aerosol scattering and absorption processes that depend on aerosol properties and environmental conditions. A detailed discussion of DL-tool inferred aerosol-radiation interaction involving aerosol micro-physics and environmental properties, is required before the article becomes acceptable for publication in ACP.

General Comments

As described, the DL tool infers multiple relationships between the EPIC sensor multi-wavelength measurements and spectral surface reflectance, sub-pixel size cloud presence, aerosol vertical distribution, aerosol particle shape and size distribution along with the complex refractive index of aerosol particles. The DL-AOD-retrieval tool is trained using unreferenced radiative transfer calculations databases in conjunction with Aerosol Robotic Network (AERONET) direct sun measurements of AOD.

The DL-tool inferred physical relationships are then used to interpret EPIC measurements in terms of AOD. The resulting inferred relationships, however, are not discussed in the manuscript. This aspect is quite important. Different inferred combinations of aerosol-relevant microphysical properties and/or environmental variables may yield similar AOD values. For instance, in the near-UV region the satellite measured radiance is driven not just by the total aerosol load, but also by the complex refractive index, and the aerosol load vertical distribution. Multiple combinations of inferred relationships based on different values of those aerosol parameters, however unrealistic, may yield AOD values close to those measured by AERONET. As reported, the AOD retrieved by the DL tool compares well

with AERONET ground-based measurements at 500 nm. DL-AERONET comparisons are statistically analyzed along with similar comparisons to AERONET using the standard MAIA the UV EPIC aerosol algorithms. Since no DL-retrievals are reported over the oceans, the usefulness of this product is limited to over-land applications.

A fundamental difference between the ML tool approach described here, and traditional physical algorithms is its computational speed. Unlike the rapid inference of physical relationships between sensor measurements and surface reflection, cloud presence, and related aerosol properties by the documented DL approach, physical algorithms carry out fully documented environmental characterizations that include surface reflective properties, cloud presence, and trace-gas absorption effects. Physical aerosol retrieval algorithms involve observation-based assumptions on aerosol particle size distribution, particle shape, aerosol composition and aerosol vertical distribution. All ancillary information used by physical algorithms is duly documented in peer-reviewed literature and algorithm theoretical basis documentation (ATBD) made available to the user community along with the released data products.

Arguably, ML-based approaches use similar ancillary databases to narrow down on the set environmental conditions, and aerosol micro-physics that explain the satellite-based observations. The science-value of the DL application to retrieve AOD, however, will be significantly enhanced if, along with the reported AOD product, information on the spatial distribution and temporal variability of DL-inferred radiatively effective radius (or any other PSD related parameter), single scattering albedo and some measure of aerosol vertical distribution such as an effective aerosol layer height. This information would increase the science value of ML applications for the utilization of satellite observations. As currently written, however, the focus of the manuscript is the reported high computational efficiency of the DL approach and, therefore, does not represent a significant contribution to the aerosol scientific community.

Since the DL-tool by itself does not specifically account for aerosol nature, explain how the different UV-absorbing aerosol types (i.e., carbonaceous particles, mineral dust, volcanic ash) are handled. How is their vertical distribution determined? Are aerosols located near the surface? In the free troposphere? stratosphere? If the DL-tool infers that information, it should be provided as part of the product instead of treating it as contained in an undecipherable black box. It may require additional human effort, but it will enhance the science value of the reported retrieval product. It would allow the user community to make informed decisions about the relevance of such measurements for practical applications such as air pollution, health quality, aviation hazards, etc.

The scientific importance of aerosol load monitoring with satellite observations is not just inferring a single number related to the aerosol load. In the retrieval process we also care about the involved physical processes which are driven by aerosol composition and environmental conditions. The standard explanation that the DL-tool learns complex non-linear relationships between satellite observations and AOD to reduce retrieval uncertainties, may be satisfactory from the purely computational perspective, but not enough from the scientific point of view that seeks not just to get an accurate AOD measurement, but doing it with the full understanding of the environmental context and the physical processes driving the interaction of the surface, the molecular atmosphere, and the different types of natural and anthropogenic aerosols in the atmosphere.

Specific comments

The abstract should be modified to include both the spatial and temporal context of the presented work.

Line 18: Not all EPIC bands are co-registered. Please refer to EPIC Level 1b documentation for the time difference between different bands.

Figure 2g: Re-do the scatter plot using the retrieved 388 nm AOD. The UV -algorithm does not carry out retrievals at 500 nm. The reported 500 nm value is a conversion. Comparisons of EPIC 388 nm AOD to AERONET 380 nm values and their diurnal variability at multiple sites are fully documented at multiple sites (Ahn et al., 2021; Torres et al., 2024) . What is the point of the Kim et al (2025) reference?

Figure 3: SHAP values of positive and negative signs (as a function of feature value) are not understood. What do negative SHAP values mean?

Figure 5: August is characterized with summer monsoon activity in Asian region. The EPIC DL-tool algorithm shows AOD (550nm) in the range 0.4-0.6 over India, whereas MODIS MAIAC shows large gaps likely due to the presence of clouds. Does the DL-tool explicitly account for and/or filter out cloudy pixels prior to aerosol inversion?

Figure 6: How are retrieval uncertainties quantified/defined? The errors are relatively larger in central/southern Africa, northern India, Southeast Asia, and part of North America, where aerosol loading is generally higher (dust and smoke). This is also quite evident in Figure 7 (a). The DL-retrieval tool tends to produce larger errors in these regions. The authors should provide a physical explanation of such DL behavior. Is it because of fewer AERONET sites/sampling that went to train the DL model? This raises another question: Did the authors derive a global DL model for aerosol retrieval from EPIC? If yes, did author attempt to regionalize the approach (i.e., lower vs. higher AOD regimes) and test its performance?

Line 45: The two shortest UV channels are designed to derive total ozone content. Is AOD also reported by the DL-tool at those wavelengths?

Line 46: The 340 and 388 channels are sensitive to UV-absorbing aerosols which include carbonaceous particles, mineral dust and volcanic ash. As a matter of fact, UV-absorbing aerosol types are easily detected via the UV aerosol index (Herman et al, 1997) over all backgrounds, including ice-snow covered surfaces and above clouds. In addition to UVAI detection capability, the UV quantitative characterization (AOD) of aerosols for cloud-free conditions (Torres et al., 1998) and its application to highly reflective backgrounds were developed (Torres et al., 2012) and extended to the visible (Jethva et al., 2013). How does the DL-tool handle instances of aerosols above either clouds or highly reflective backgrounds?

Line 47: Only land-vegetated surfaces are darker in the UV than in the visible. Water surfaces, however, are brighter in the UV than in the visible.

Line 48: The UV retrieval capability of absorbing aerosol properties does not come from the low surface reflectance. It is based on the absorption by aerosol particles of Rayleigh scattered UV radiation as illustrated qualitatively by the well know UV Aerosol Index (UVAI) parameter. Over snow covered surfaces and above clouds the aerosol absorption signal is further enhanced.

Line 49: Radiance measurements in the O2A/B bands are sensitive to aerosol layer height, not to its vertical distribution.

Lines 50-51: O2 absorption bands cannot directly retrieve aerosol vertical profiles.

Line 53: The EPIC UV-based algorithm is introduced but not described. A brief description should be included: It retrieves simultaneously AOD and single scattering albedo (SSA) at 388 nm using aerosol layer height (ALH) retrieved from Oxygen-B band observation. Also retrieves above cloud aerosol optical depth, and absorption-corrected cloud optical depth (Torres et al., 2012).

Line 55: What does high UVAI mean? The UVAI concept has not even been introduced in the manuscript.

Line 62: Cite relevant sources of meteorological and environmental variables that are integrated as input features. Discuss aerosol layer height and single scattering albedo assumptions (or DL inferences) in particular.

Line 65: Discuss resulting DL-tool inferences. In addition to AOD, aerosol science applications require also information on aerosol physical properties (particle size distribution, wavelength-dependent complex refractive index) along with aerosol vertical

distribution and surface reflectance. When not directly retrieved, this information is inferred by physical algorithm developers based on independent observations and made publicly available to data users via algorithm documentation such as associated readme files and peer-reviewed literature. As stated by the authors, the DL technique implicitly accounts for the physical interaction of incoming light and aerosol properties leading to the calculated AOD. The DL aerosol product should, therefore, document the inferred aerosol microphysical properties along with the spatial and temporal context of generated AOD product.

lines 67-69: Combine these two statements into a single one.

Line 70: Discuss features of the DL-tool inferred SSA and ALH fields.

Line 83: Describe the process of removing cloud-contaminated pixels. How are aerosols above clouds handled? Carbonaceous aerosols above clouds yield a very high UVAI signal. How are those scenes handled by the DL-tool?

Line 197: The EPIC UV-algorithm does not retrieve AOD at 500 nm. The actual retrieval is carried out at 388 nm. The 500 nm is a converted value. The 388 nm AOD value should be used in this analysis.

Line 218-220: Elaborate on the handling of information content of the 340 and 388 measurements. The attenuation effect reflectance measurements in the UV is driven not just by the aerosol amount, but also by the single scattering albedo and aerosol layer height.

References

Herman, J. R., Bhartia, P. K., Torres, O., Hsu, N. C., Seftor, C. J., & Celarier, E. (1997). Global distribution of UV-absorbing aerosols from Nimbus 7/TOMS data. *Journal of Geophysical Research*, *102*(16), 16911–16922. https://doi.org/10.1029/96jd03680

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Torres, O., & Ahn, C. (2024). Local and regional diurnal variability of aerosol properties retrieved by DSCOVR/EPIC UV algorithm. *Journal of Geophysical Research: Atmospheres*, *129*, e2023JD039908. https://doi.org/10.1029/2023JD039908