

Version 2 of hourly aerosol optical centroid height (AOCH) data product from EPIC/DSCOVR in deep space

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ABSTRACT

Orbiting at Sun-Earth Lagrange-1 point, the Earth Polychromatic Imaging Camera (EPIC) provides sunlit Earth images at 10 channels from ultraviolet (UV) to near-infrared (NIR) every 1–2 h. Here, we presented the version 2 of the algorithm to retrieve aerosol optical depth (AOD) and aerosol optical centroid height (AOCH) from visible (443 and 680 nm) and O₂ absorption (688 and 764 nm) bands of EPIC (hereafter AOCH-v2 algorithm). The EPIC AOCH-v2 algorithm differs from the version 1 (AOCH-v1) algorithm in several aspects. First, an independent calculation of ultraviolet aerosol index (UVAI) was added by using two UV bands (340 and 388 nm) to identify absorbing aerosols for AOCH retrieval. Second, we updated the real part of aerosol refractive index to represent a new smoke aerosol model for large smoke AOD scenarios over North America, while retaining the original smoke model generated from the Aerosol Robotic Network (AERONET) climatology for background aerosol cases. Third, a new AOD retrieval scheme was developed to constrain the surface reflectance using the climatological surface reflectance ratios. Finally, the cloud mask scheme was improved for cloud screening over bright surfaces. The EPIC AOD from the AOCH-v2 algorithm displays a better agreement with AERONET than AOCH-v1 algorithm. The evaluations against Cloud-Aerosol Lidar with Orthogonal Polarization (CALIOP) measurements indicate that the AOCH overestimation in AOCH-v1 algorithm is significantly mitigated by AOCH-v2 algorithm, suggesting uncertainties in the EPIC AOCH retrievals are notably reduced through a better characterization of surface reflectance, enhanced AOD retrievals, and an updated smoke aerosol model.

1. Introduction

The total column loading and vertical distribution of aerosols are both essential parameters for studying the impacts of aerosols on the ecosystem, climate and surface air quality (Val Martin et al., 2013; Wang and Christopher, 2003; Yu et al., 2015; Zarzycki and Bond, 2010). Observations of aerosols from ground-based, airborne and spaceborne instruments have significantly improved our understanding of the roles that aerosols play in the environmental and climate system. However, surface and aircraft measurements are limited in their spatial or temporal coverage to fully measure the variations of aerosol properties on a global scale (Diner et al., 2004). Currently, satellite remote sensing is the only way to obtain observational global distribution of aerosol optical depth (AOD) and aerosol layer height (ALH) on a daily basis (Kim et al.,

2025). The retrievals of aerosol properties from satellite sensors on low Earth orbit (LEO), such as Moderate Resolution Imaging Spectroradiometer (MODIS), Visible Infrared Imaging Radiometer Suite (VIIRS) and Tropospheric Monitoring Instrument (TROPOMI), have significantly improved our understanding of the spatial and temporal distribution, the sources and transport, and environmental and climate impacts of aerosols over the past two decades (Hsu et al., 2013; Hsu et al., 2004; Jackson et al., 2013; Kaufman et al., 1997; Levy et al., 2007; Lyapustin et al., 2018; Torres et al., 2020). However, there is a dearth of global retrieval of aerosol vertical distribution from spaceborne instruments. This is because active sensors are spatially sparse (Winker et al., 2009; Yorks et al., 2016) and passive sensors tend to yield relatively larger uncertainty (Nanda et al., 2020; Park et al., 2016; Xu et al., 2018).

Several algorithms have been developed to retrieve ALH using

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different passive remote sensing techniques, such as stereoscopic photogrammetry (Nelson et al., 2013), infrared thermal technique (Lyapustin et al., 2020; Vandenbussche et al., 2013), polarization measurements in ultraviolet (UV) or deep blue bands (Wu et al., 2016), oxygen or oxygen-dimer absorption spectroscopy (Lyapustin et al., 2025; Park et al., 2025; Zhang et al., 2025) and machine learning technique (Tian et al., 2024). However, passive ALH retrieval remains challenging due to inherent observational and methodological limitations. These include limited temporal sampling from sun-synchronous satellites (Nanda et al., 2019; Nelson et al., 2013; Vandenbussche et al., 2013) versus incomplete spatial coverage from geostationary platforms (Park et al., 2025; Zhang et al., 2025), method-dependent sensitivities arising from specific physical assumptions or favorable observational conditions (e.g., spatial variability and texture contrast of aerosol plumes for stereoscopic approaches (Nelson et al., 2013) and assumptions of surface emissivity and temperature profile for infrared techniques (Lyapustin et al., 2020; Vandenbussche et al., 2013)), and reduced generalization capability of data-driven methods under unseen conditions (Tian et al., 2024). These factors collectively contribute to substantial uncertainties and limited spatiotemporal representativeness of retrieved ALH across different approaches.

In this paper, we present the 2nd version of the AOC algorithm (AOC-v2) for Earth Polychromatic Imaging Camera (EPIC), which showed improved retrieval performance for AOD and aerosol optical centroid height (AOC) over the AOC-v1 algorithm. AOC is defined as the altitude where the aerosol extinction peaks under the assumption of quasi-Gaussian distribution of aerosol extinction profile (Xu et al., 2019; Xu et al., 2017). The EPIC AOC product is specifically designed for absorbing aerosols, i.e., smoke and dust, which are often transported into the free troposphere and can exert substantial impacts on climate, air quality, and ecosystems through long-range transport (Torres et al., 2012). Onboard the Deep Space Climate Observatory (DSCOVR) satellite, EPIC measures the sunlit side of the Earth at 10 spectral bands every 1–2 h from deep space at the Lagrange-1 point (Marshak et al., 2018). These spectral channels range from UV to near-infrared (NIR) bands including O₂ A (764 nm) and B (688 nm) bands that are sensitive to aerosol vertical distribution. Based on the research algorithm for retrieving AOD and AOC from EPIC (Lu et al., 2021; Xu et al., 2019; Xu et al., 2017), we developed the AOC-v1 operational product in 2022 and published it at National Aeronautics and Space Administration (NASA) Langley Research Center Atmospheric Science Data Center (https://asdc.larc.nasa.gov/project/DSCOVR/DSCOVR_EPIC_L2_AOC_01).

Compared with conventional LEO satellite sensors such as MODIS and TROPOMI, which usually offer only one observation per day over a given location, EPIC provides near-hourly observations of the entire sunlit hemisphere from the Earth-Sun Lagrange-1 point. This unique viewing geometry enables continuous monitoring of the rapid evolution and long-range transport of elevated aerosol plumes at regional to hemispheric scales, while also enabling characterization of diurnal variations of ALH and the construction of long-term climatological records over fixed regions (Ahn et al., 2021; Lu et al., 2023a; Lu et al., 2021; Xu et al., 2019; Xu et al., 2017), offering observational capabilities that are not available from LEO platforms.

Although AOC-v1 demonstrated the feasibility of retrieving AOC from EPIC observations, its performance was limited by uncertainties in cloud screening, aerosol optical models and characterization of surface reflectance, motivating the development of AOC-v2. The AOC-v2 retrieval algorithm includes the following key updates: (a) modification of cloud masking scheme to improve cloud screening over bright surfaces; (b) addition of a smoke aerosol optical model for large AOD conditions; (c) design of an iterative scheme to constrain AOD retrieval by the surface reflectance ratios; (d) calculation of UV aerosol index (UVAI) with reduced artifacts at the edge of EPIC field of regard (FOR). We evaluated the AOD retrieval from AOC-v2 algorithm against collocated Aerosol Robotic Network (AERONET) AOD data. The AOC

retrievals from AOC-v2 algorithm are validated using Cloud-Aerosol Lidar with Orthogonal Polarization (CALIOP) measurements. A comprehensive intercomparison with other ALH retrieval algorithms, including comparisons of large-scale spatial patterns, seasonal and interannual variations, overall statistics from pixel-by-pixel comparisons and benchmark case evaluations, is beyond the scope of this study and will be addressed in future work. We also compared the UVAI from our AOC-v2 algorithm with that from EPIC near-UV aerosol (EPICAERUV) algorithm (Ahn et al., 2021).

By bridging the spatial gaps of active lidars and the temporal constraints of conventional LEO passive sensors, the EPIC AOC-v2 product provides a unique observational constraint on the vertical distribution of absorbing aerosols. It is helpful for understanding surface air quality impacts associated with long-range transported smoke and dust (Chen et al., 2021; Val Martin et al., 2013). It also supports the improved quantification of aerosol radiative forcing in climate models (Ge et al., 2014; Zarzycki and Bond, 2010; Zhang et al., 2013), as well as evaluations of aerosol impacts on ecosystems and environmental systems through modulating atmospheric composition and deposition processes (Rizzolo et al., 2017; Yu et al., 2015; Yu et al., 2019).

The rest of this paper is organized as follows. Section 2 introduces the features of EPIC instrument and EPIC level 1B data as well as other datasets used in this study. The new development of the algorithm is described in Section 3, including the updates of cloud screening scheme, the new smoke aerosol model, the derivation of the surface reflectance ratio and new algorithm for retrieving AOD and AOC. Section 4 shows the evaluation results of AOD, AOC and UVAI from the new algorithm. The summary is displayed in Section 5.

2. Datasets

2.1. EPIC L1B data

EPIC is a multi-spectral imager onboard the DSCOVR satellite, which was launched to the Sun-Earth Lagrange-1 orbit in February of 2015. It provides the sunlit Earth disk measurements of backscattered solar radiance at 10 channels from UV to NIR every 1–2 h using a 30-cm aperture Cassegrain telescope. The frequency of the measurements depends on the season. The spatial resolution of the EPIC measurements is ~10 km at nadir and ~20 km at the viewing zenith angle of 60°. Due to the special geometric relationship among Sun, Earth and the EPIC instrument, the scattering angle of EPIC observation is almost constant ranging from 168.5° to 175.5°. More details on the features of the EPIC instrument can be found at Marshak et al. (2018).

Our AOC-v2 uses the level 1B measurements at 8 bands to retrieve the AOD, AOC and UVAI on a near-hourly basis. The 340 nm and 388 nm channels are used for calculating UVAI (Herman et al., 1997; Torres et al., 1998). The cloud mask involves the EPIC bands of 443 nm, 551 nm and 780 nm (Xu et al., 2019). We use blue (443 nm) and red (680 nm) to retrieve AOD. The AOC is retrieved using the ratios of two O₂ absorption bands to their respective neighboring continuum bands, i.e., 688 nm/680 nm for O₂ B-band and 764 nm/780 nm for O₂ A-band. We scaled the EPIC 680 nm and 688 nm bands by −6.6% and +3.0%, respectively, as the vicarious calibration following Lu et al. (2021). The other spectral bands were used without additional vicarious calibration, relying on the standard EPIC level 1B calibration (Geogdzhayev and Marshak, 2018; Marshak et al., 2018).

2.2. AERONET data

The AERONET version 3 level 2.0 AOD product (Giles et al., 2019; Holben et al., 1998) was used for the evaluation of the EPIC AOD retrievals. The AERONET AOD is retrieved from the direct sun measurements by ground-based sun photometers following the Beer-Lambert-Bouguer law. Under cloud-free conditions, the uncertainty of AERONET AOD is within 0.01 at the wavelength longer than 0.44 μm from a

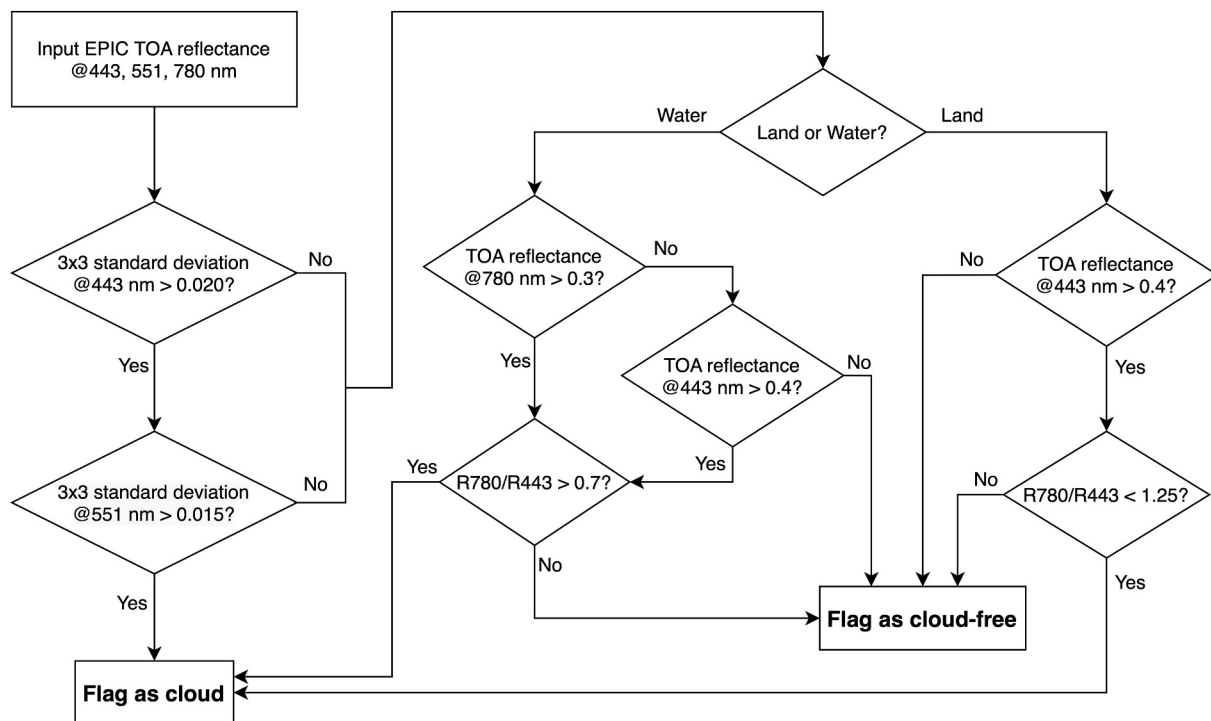


Fig. 1. Flowchart of the cloud mask scheme for EPIC AOC-v2 algorithm.

newly calibrated instrument, and the AERONET instruments are routinely calibrated at least twice per year (Holben et al., 1998). The EPIC AOD at 680 nm within 50 km of each AERONET site are compared with the 675 nm AOD within 30 min of EPIC overpass time from each corresponding AERONET site following Lyapustin et al. (2021). The selection of 680 nm instead of 551 nm as the primary evaluation wavelength enables a direct comparison with AERONET's physically measured 675 nm AOD, which avoids the secondary interpolation errors and severe data loss inherent to the derived AERONET 551 nm AOD (Eck et al., 1999; Giles et al., 2019; Remer et al., 2005). Besides, the 680 nm AOD serves as the direct radiative anchor that physically constrains the AOC_H retrieval relying on the O₂ B band ratio (688 nm/680 nm). Evaluating AOD at 680 nm is a necessity to ensure the self-consistency and accuracy of the entire coupled AOC_H-v2 retrieval framework. The AOD difference due to the wavelength shift between 680 nm and 675 nm is typically below 1.5%. For instance, the AOD difference is 1.11–1.49% for smoke aerosols with an Ångström exponent of 1.5–2.0, and 0–0.37% for dust aerosols with an Ångström exponent of 0–0.5 (Ångström, 1961; Ångström, 1929; Dubovik et al., 2002; Hess et al., 1998). This AOD difference is much smaller than other uncertainty sources in the retrieval and validation processes. In addition, spectral conversion using the Ångström exponent introduces additional assumptions and uncertainties regarding the spectral dependence of AOD (Eck et al., 1999). Therefore, the nearest available AERONET wavelength (675 nm) was directly used in this study.

The microphysical and optical properties, including refractive index, size distribution parameters (effective radius and effective variance of bimodal lognormal distribution), fine mode fraction, single scattering albedo and phase function, from AERONET inversion product (Dubovik and King, 2000; Sinyuk et al., 2020) for thick smoke cases are compared with the counterparts of the old smoke aerosol model used in EPIC AOCH-v1 algorithm, in order to diagnose the AOD retrievals for smoke aerosols over North America from EPIC AOCH-v1 (Section 3.2).

2.3. CALIOP and MERRA-2 aerosol extinction profile

CALIOP was an elastic backscatter lidar onboard the satellite Cloud-

Aerosol Lidar and Infrared Pathfinder Satellite Observation (CALIPSO). In 2006–2023, it was placed at a sun-synchronous orbit with an overpass time of $\sim 13:30$ local time and a repeat cycle of 16 days. The swath width of CALIOP measurements is as narrow as ~ 90 m (Winker et al., 2009). The aerosol extinction coefficient profile at 532 nm from CALIOP level 2 Aerosol Profile product (version 4–51) and level 3 Tropospheric Aerosol Profile product (version 4–21) (Winker et al., 2013) was used for the evaluation of EPIC AOC retrievals. The level 2 and level 3 products serve complementary objectives. CALIOP level 2 data were used for spatially and temporally collocated pixel-level validation of individual EPIC AOC retrievals, which evaluates the retrieval fidelity of EPIC AOC at the instantaneous observation scale. In contrast, CALIOP level 3 monthly gridded product was used for comparison of annual mean spatial patterns at the global scale, which evaluates the climatological representativeness and large-scale spatial consistency of the EPIC AOC product. Although CALIOP is subject to uncertainties associated with daytime solar background noise, cloud-aerosol discrimination and lidar ratio assumptions, extensive validation against independent ground-based and airborne lidar observations has demonstrated its ability to accurately characterize aerosol vertical structure and layer heights (Mamouri et al., 2009; Papagiannopoulos et al., 2016; Pappalardo et al., 2010; Rogers et al., 2011; Winker et al., 2013). Consequently, CALIOP products have been widely used as benchmark for evaluating the ALH retrievals from passive satellite remote sensing (Chen et al., 2021; Chimot et al., 2018; Kim et al., 2025; Lu et al., 2021; Xu et al., 2019).

The CALIOP level 2 Aerosol Profile product features a spatial resolution of 5 km horizontally and 60 m vertically, while the level 3 Tropospheric Aerosol Profile product has a horizontal resolution of $2^\circ \times 5^\circ$ and the same 60 m vertical resolution. To facilitate the comparison of CALIOP aerosol extinction profile with the EPIC AOC retrieval, we calculated an optical depth weighted height from CALIOP data using Eq. (1) following Lu et al. (2023a).

$$AOCH_{\text{CALIOP}} = \frac{\sum_{i=1}^n \beta_{\text{ext},i} \Delta Z_i Z_i}{\sum_{i=1}^n \beta_{\text{ext},i} \Delta Z_i} \quad (1)$$

Here $\beta_{\text{ext},i}$ is aerosol extinction coefficient at 532 nm at vertical layer i with the altitude of Z_i , and ΔZ_i is the layer thickness of vertical layer i . The CALIOP AOC in this study differs from the CALIOP-based ALH definition in [Torres et al. \(2013\)](#), which was defined as the attenuated-backscatter-weighted height. The attenuated backscatter signal is not equivalent to aerosol backscatter alone, but includes contributions from all extinction processes above a given altitude, and is modulated by the two-way atmospheric transmittance. In addition, optical depth weighted height used in this study directly reflects the vertical distribution of AOD and does not correspond to a backscatter or extinction weighted height when the vertical resolution is non-uniform due to their different physical weighting kernels.

In addition to CALIOP, we also calculated AOC from MERRA-2 aerosol extinction profiles following Eq. (1) for comparison with EPIC AOC. MERRA-2 provides a global aerosol reanalysis dataset that assimilates satellite aerosol observations within the GEOS-5 modeling framework with a horizontal resolution of $0.5^\circ \times 0.625^\circ$ ([Gelaro et al., 2017](#)). The MERRA-2 AOC is included to provide additional context for evaluating the performance of the EPIC AOC retrievals relative to a state-of-the-art model-based aerosol product and to assess the potential value of EPIC AOC for constraining model-simulated aerosol vertical distributions.

3. Algorithm development

3.1. New cloud mask scheme

We designed a new cloud screening scheme and applied it in the EPIC AOC-v2 algorithm. The EPIC AOC-v1 algorithm implemented cloud mask via spatial variability tests at 443 nm and 551 nm over both land and water surfaces, along with the brightness tests at 443 nm and 680 nm for land surfaces or at 443 nm, 680 nm and 780 nm for water surfaces ([Xu et al., 2019](#)). The underlying principle is that clouds generally exhibit higher spatial heterogeneity and higher reflectance than cloud-free areas ([Ackerman et al., 1998](#)). Only the pixel passing all these tests is identified as a clear pixel, otherwise it is flagged as cloud-contaminated pixel. This scheme is found to have challenges to distinguish the thick aerosol plume from clouds and bright surfaces ([Lu et al., 2023a; Lu et al., 2021](#)). Tuning the thresholds of different cloud detection tests in the old scheme usually results in either being too aggressive, misclassifying the thick aerosol plumes or clear pixels with bright surfaces as clouds, or too lenient, failing to detect some thin and scattered cloud pixels. To address this problem, we updated the cloud screening scheme. [Fig. 1](#) displays the flowchart of the new cloud mask scheme used in the EPIC AOC-v2 algorithm. The brightness test at 680 nm was removed due to the high surface reflectance over arid or semi-arid area, which causes the ambiguity between bright surfaces and clouds. We added a new cloud detection test using the ratio of NIR band (780 nm) to visible (VIS) band (443 nm). The NIR-to-VIS ratio test is based on the distinct spectral signatures of clouds, land, and water surfaces across visible and near-infrared wavelengths. For cloud-free water surfaces, the top-of-atmosphere (TOA) reflectance at 443 nm is significantly larger than that at 780 nm because of the stronger Rayleigh scattering and aerosol scattering at shorter wavelength. For most cloud-free land surfaces except snow and ice, surface reflectance generally increases dramatically from 443 nm to 780 nm ([Baldridge et al., 2009](#)). For clouds, the reflectance value is similar between 443 and 780 nm. Therefore, the ratio of 780 nm band to 443 nm band is close to 1 over clouds, significantly lower than 1 over cloud-free water surfaces and larger than 1 over cloud-free land surfaces ([Saunders and Kriebel, 1988](#)). Similar NIR/VIS reflectance ratio tests have also been widely implemented in operational cloud mask algorithms such as MODIS cloud mask over diverse surface types including vegetation, bare soil and desert surfaces ([Ackerman et al., 2010; Ackerman et al., 1998](#)). The threshold values for the cloud masking tests were determined empirically based on statistical analysis of representative clear-sky and cloudy scenes for different

Table 1

Comparison of cloud detection tests between AOC-v1 and AOC-v2 algorithms.

		Cloud Mask v1	Cloud Mask v2
Spatial Variability Test	S443 ^a	L&W ^b : > 0.015	L&W: > 0.020
	S551	L&W: > 0.010	L&W: > 0.015
	R443 ^c	L&W: > 0.40	L&W: > 0.40
Brightness Test	R680	L: > 0.45; W: > 0.40	Not used
	R780	W: > 0.35	W: > 0.30
	R780/R443	Not used	L: < 1.25; W: > 0.70

^a S443 denotes the 3×3 spatial standard deviation of TOA reflectance at 443 nm. The same definition applies for other wavelengths.

^b L represents land surface, and W represents water surface.

^c R443 denotes the TOA reflectance at 443 nm. The same definition applies for other wavelengths.

surface types and viewing geometries. The logic flow of these tests is also redesigned. A pixel will be flagged as cloud if it fails the spatial variability test or fails both the brightness test and NIR/VIS test. The failure of the spatial variability test is defined as the failure at both 443 nm and 551 nm. For water surfaces, the failure of brightness test is defined as the failure at either 443 nm or 780 nm. [Table 1](#) compares the cloud detection tests used in AOC-v1 and AOC-v2 algorithms.

[Fig. 2](#) presents the comparison of cloud masks between EPIC AOC-v2 and AOC-v1 algorithms for two cases. The first case ([Fig. 2\(a-c\)](#)) is on Aug. 14, 2020, at 08:04 UTC, when the EPIC image was centered over the Arabian Peninsula. As marked by the red ellipse, the v1 scheme misclassified a large cloud-free area over the bright surfaces of North Africa and Arabian Peninsula as clouds. In v2 algorithm, this misclassification has been corrected. The second case ([Fig. 2\(d-f\)](#)) covering North America on Aug. 14, 2020, at 18:59 UTC, shows that the v2 scheme identifies more cloud-free pixels along the cloud edges, while the v1 scheme was too aggressive to distinguish the cloud-free area over the bright surface of Western US. This result demonstrates the improved capability of v2 algorithm to distinguish the cloud-free area from clouds compared to v1 scheme, because the new cloud detection tests and logic flow in v2 scheme rely less on the simple brightness thresholds than those in v1 scheme. Besides, [Fig. 2](#) indicates that the v2 cloud mask scheme correctly identifies more cloud-free area over water surfaces than v1 scheme. In this study, the cloud mask is developed as a pre-processing step for aerosol retrieval rather than as an independent cloud classification product. Due to the relatively large footprint of EPIC observations, the associated sub-pixel cloud contamination ([Yang et al., 2019](#)), and the absence of thermal infrared channels that provide critical information for cloud detection, cloud masking for EPIC observations is inherently challenging, and reliable pixel-level ground truth for EPIC observations is not readily available for rigorous quantitative validation. Therefore, the effectiveness of the cloud mask is evaluated mainly through visual inspection of representative case studies and partly reflected in the quality of aerosol retrievals evaluated in [Section 4](#).

3.2. New smoke aerosol model

We updated the original smoke aerosol model based on AERONET data. The original smoke aerosol model used in AOC-v1 algorithm tends to underestimate the AOD especially for the large AOD cases, which indicates the original smoke aerosol model overestimates the aerosol single scattering. We investigated aerosol microphysical and optical properties from AERONET sites REXburgIdaho and Cascade_Airport for the heavy smoke case on August 21, 2020, and compared them with our original smoke aerosol model ([Table 2](#) and [Fig. 3](#)). The single scattering albedo (SSA) and phase function are compared only at 443 nm and 680 nm, since we used these two EPIC channels to retrieve AOD. We ignored the spectral variation between the EPIC band 443 nm

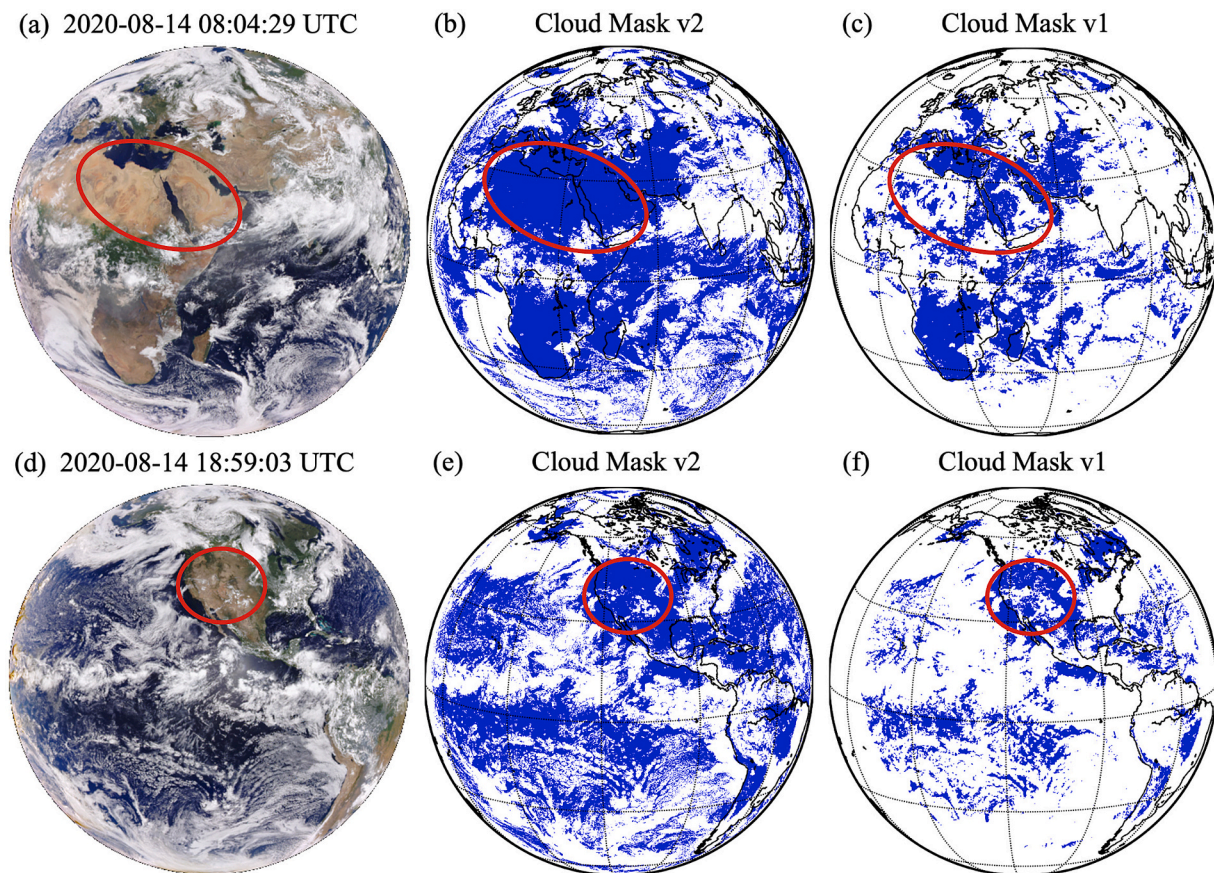


Fig. 2. Comparison of cloud masks from EPIC AOCCH-v2 and AOCCH-v1 algorithms. (a) EPIC true color image for Aug. 14, 2020, at 08:04:29 UTC. (b) Cloud mask from EPIC AOCCH-v2 algorithm, where blue represents cloud-free area and white represents cloudy region. (c) Cloud mask from EPIC AOCCH-v1 algorithm. (d–f) Same as (a–c), but for Aug. 14, 2020, at 18:59:03 UTC. The red ellipses highlight the improvements of cloud mask in v2 algorithm compared to v1 algorithm. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 2

Comparison of smoke aerosol microphysical and optical properties at 443 nm and 680 nm used in the AOD retrieval.

	AERONET	Original LUT
Refractive index @443 nm	1.428–0.0095i	1.550–0.0070i
Refractive index @680 nm	1.459–0.0090i	1.550–0.0070i
Effective radius [μm] (fine)	0.156	0.236
Effective variance (fine)	0.154	0.175
Effective radius [μm] (coarse)	2.817	3.703
Effective variance (coarse)	0.395	0.464
Fine mode fraction (volume)	0.781	0.915
SSA @ 443 nm	0.938	0.939
SSA @ 680 nm	0.926	0.945

and AERONET band 440 nm, as well as EPIC band 680 nm versus AERONET band 675 nm. The SSA of heavy smokes from AERONET sites is comparable with that of the original smoke aerosol model (0.938 vs 0.939 at 443 nm and 0.926 vs 0.945 at 680 nm), but the AERONET phase function is significantly lower than that of the original smoke aerosol model at the backscattering direction (scattering angle of $\sim 175^\circ$) by 58.8% and 41.8% at 443 nm (Fig. 3(a)) and 680 nm (Fig. 3(c)), respectively. This discrepancy can well explain the underestimation of the EPIC AOD since the EPIC observations feature an almost constant scattering angle between 168.5° and 175.5° (Marshak et al., 2018), as indicated by the light blue shaded area in each panel of Fig. 3.

We calculated an updated phase function using Mie code with all the microphysical parameters replaced by the counterpart of AERONET measurements in Table 2 for both 443 nm (Fig. 3(a)) and 680 nm (Fig. 3

(c)). The updated phase functions display a good agreement with the AERONET data at the backscattering direction at both wavelengths. The key microphysical property leading to the discrepancy of the phase function between original aerosol model and AERONET at the backscattering direction is then identified by a sensitivity test at 443 nm (Fig. 3(b)) and 680 nm (Fig. 3(d)). In this sensitivity test, we examined multiple parameters including real and imaginary part of refractive index, effective radius, effective variance and fine mode fraction. Each time, we replaced one microphysical parameter of the original aerosol model with the counterpart of AERONET measurement in Table 2 and calculated the phase function using Mie code. Each calculated phase function was compared with the original phase function and the updated phase function with all parameters replaced. Fig. 3(b) and Fig. 3(d) show only the phase function with the real part refractive index updated agrees with the updated phase function with all parameters replaced well at both 443 nm and 680 nm. Therefore, the real part refractive index is the key parameter that causes the discrepancy of the phase function at the backscattering direction.

We updated the real part refractive index from 1.550 to 1.459 to generate a new smoke aerosol model for large smoke AOD scenarios over North America. The update is informed by the sensitivity analysis based on a representative heavy smoke transport event. Therefore, the revision is not a direct and full adoption of a single case, but a sensitivity-guided refinement of the aerosol model. The original aerosol model generated from the AERONET climatology is used for the background aerosols. To quantify the impact of new smoke aerosol model on the EPIC AOD retrieval, we evaluated the AOD retrievals against AERONET AOD for 2020 August over North America ($140^\circ\text{W} - 60^\circ\text{W}$, $25^\circ\text{N} - 60^\circ\text{N}$) using new AOD retrieval scheme (Section 3.4) with original smoke lookup

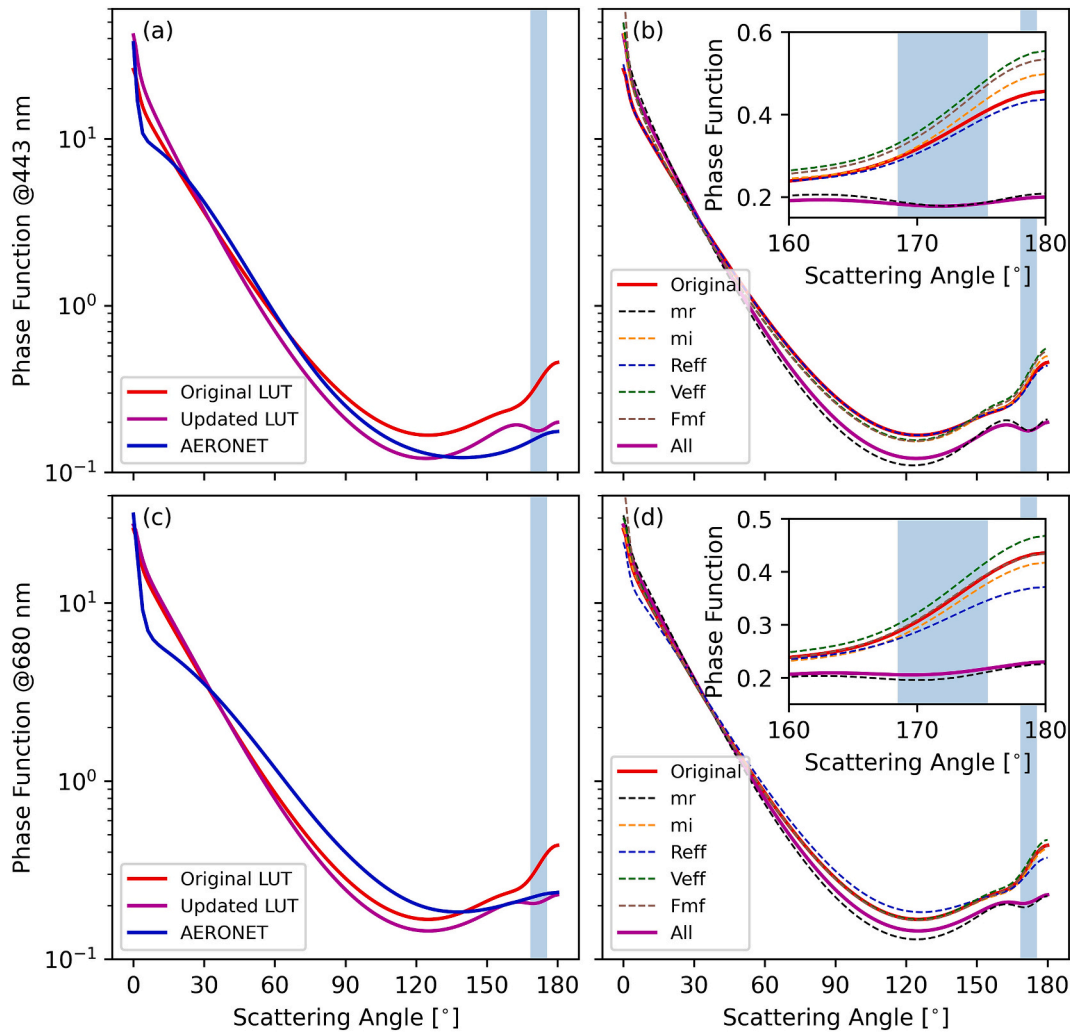


Fig. 3. (a): Comparison of the phase function at 443 nm from original smoke aerosol model (red), updated aerosol model (pink) and mean value (blue) from AERONET sites Rexburg_Idaho and Cascade_Airport for the heavy smoke case on August 21, 2020. (b): The 443 nm phase functions from the Mie calculations for the original aerosol model (red solid), and for models with individual parameters replaced by their corresponding AERONET values: real (black dash) and imaginary (orange dash) part of refractive index, effective radius (blue dash), effective variance (green dash) and fine mode fraction (brown dash). The phase function with all of the above parameters simultaneously replaced by the AERONET counterparts listed in Table 2 is shown by the pink solid line. The inset shows the zoomed-in view for the scattering angle from 160° to 180°. (c-d): Same as (a-b) but for 680 nm. The light blue shaded area in each panel indicates the range of EPIC scattering angle between 168.5° and 175.5°.

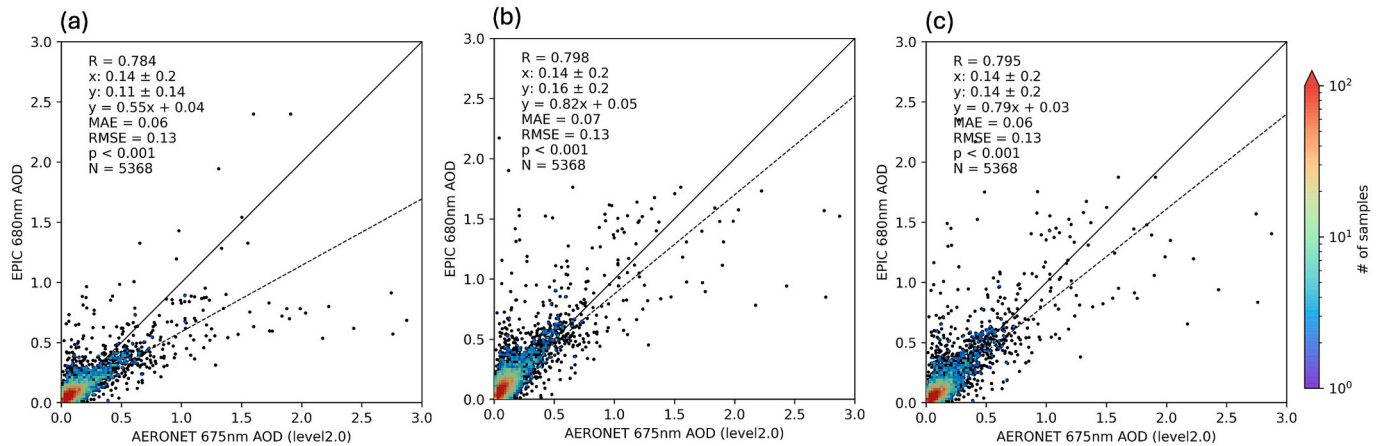


Fig. 4. (a) Comparison of EPIC AOD retrievals using the new retrieval scheme (Section 3.4) with original smoke aerosol model against AERONET AOD for 2020 August over North America (140°W - 60°W, 25°N - 60°N). (b) Same as (a) but with updated smoke aerosol model. (c) Same as (a) but using a combination of original and updated smoke aerosol models.

table only (Fig. 4(a)), updated lookup table only (Fig. 4(b)) and a combination of two lookup tables (Fig. 4(c)). Compared to the original smoke aerosol model, the updated aerosol model substantially improves the agreement between EPIC AOD and AERONET observations, with the regression slope increasing from 0.55 to 0.82, indicating a significant reduction in the overestimation of aerosol backscattering in the aerosol model, thus mitigating the underestimation of AOD retrievals for large AOD cases. However, the updated aerosol model also introduces a slight positive bias under low-AOD conditions. The mean bias error increased from -0.03 to $+0.02$ and the mean absolute error increased by 0.01 . To better represent the full range of aerosol conditions encountered over North America during wildfire events, we combined the original and updated smoke aerosol models in the new retrieval algorithm (Section 3.4). As shown in Fig. 4(c), the combined retrieval approach largely preserves the improvement in regression slope achieved by the updated smoke aerosol model while reducing the positive bias for low AOD cases, resulting in a more balanced overall retrieval performance across both background and heavy smoke conditions with the mean bias error remaining within ± 0.01 . These results demonstrate that the updated lookup table combined with the original one provide a more robust and physically consistent representation of aerosol optical properties for EPIC AOD retrievals.

3.3. Derivation of surface reflectance ratio

The treatment of surface reflectance is crucial for satellite AOD retrievals (Hsu et al., 2004; Kaufman et al., 1997) and therefore, needs to be carefully considered because the EPIC AOD retrieval depends on the AOD retrieval (Xu et al., 2019; Xu et al., 2017). Generally, an underestimation of AOD leads to an overestimation of AODCH, except for the conditions of dark surfaces (surface reflectance < 0.02) and AODCH lower than 3 km (Xu et al., 2019; Xu et al., 2017). To improve the AODCH retrieval, we constrained the AOD retrieval using the ratio of surface reflectance at different EPIC bands in AODCH-v2 algorithm. A lot of previous studies on AOD retrieval use the prescribed spectral relationship of the surface reflectance between visible and shortwave infrared channels to characterize the surface reflectance at visible band, taking advantage of the low aerosol contributions to the shortwave infrared bands (Drury et al., 2008; Hsu et al., 2013; Kaufman et al., 1997; Levy et al., 2007; Wang et al., 2010). While the shortwave infrared band at $2.12 \mu\text{m}$ from MODIS (Levy et al., 2007) and $2.25 \mu\text{m}$ (M11) from VIIRS

(Hsu et al., 2019) are generally used, the EPIC band with the longest wavelength is only $0.78 \mu\text{m}$. However, there are also successful practices that use the wavelengths much shorter than $2.1 \mu\text{m}$. Hsu et al. (2013) applied the deep blue aerosol algorithm to the Sea-viewing Wide Field-of-view Sensor (SeaWiFS) measurements by using the surface reflectance ratio between visible bands and $0.865 \mu\text{m}$ over vegetated areas. Zhang et al. (2016) used the surface reflectance ratio between VIIRS bands M3 vs M5 ($0.488 \mu\text{m}$ vs $0.672 \mu\text{m}$) to constrain the AOD retrieval. Therefore, we determined to use surface reflectance ratio of 443 nm to 680 nm and 443 nm to 780 nm in EPIC AODCH-v2 algorithm.

The surface reflectance ratio was derived for each pixel based on the simplified radiative transfer equation and the lower envelope method (Drury et al., 2008). The simplified radiative transfer equation can be expressed as

$$\rho_{\lambda}^*(\theta_0, \theta, \phi) = \rho_{\lambda}^a(\theta_0, \theta, \phi) + \frac{F_{\lambda}(\theta_0)T_{\lambda}(\theta)}{1 - s_{\lambda}\rho_{\lambda}^s(\theta_0, \theta, \phi)}\rho_{\lambda}^s(\theta_0, \theta, \phi) \quad (2)$$

where $\rho_{\lambda}^*(\theta_0, \theta, \phi)$ is TOA reflectance as a function of solar zenith angle θ_0 , viewing zenith angle θ and relative azimuth angle ϕ at wavelength λ ; $\rho_{\lambda}^a(\theta_0, \theta, \phi)$ is atmospheric reflectance; $\rho_{\lambda}^s(\theta_0, \theta, \phi)$ is surface bidirectional reflectance distribution function (BRDF); $F_{\lambda}(\theta_0)$ and $T_{\lambda}(\theta)$ are downward and upward atmospheric transmittance respectively; and s_{λ} is the atmospheric reflectance for upward radiation. For instance, denote the surface reflectance ratio of 443 nm to 680 nm as k , i.e.,

$$\rho_{443}^s(\theta_0, \theta, \phi) = k\rho_{680}^s(\theta_0, \theta, \phi) \quad (3)$$

Based on Eq. (2) and (3), for low AOD and cloud-free condition we have

$$\rho_{443}^*(\theta_0, \theta, \phi) = \frac{\tau_{443}\omega_{443}P_{443}(\theta_0, \theta, \phi)}{\mu_0\mu} + F_{443}(\theta_0)T_{443}(\theta)\rho_{443}^s(\theta_0, \theta, \phi) \quad (4)$$

$$\rho_{443}^*(\theta_0, \theta, \phi)\mu_0\mu = \tau_{443}\omega_{443}P_{443}(\theta_0, \theta, \phi) + kF_{443}(\theta_0)T_{443}(\theta)\rho_{680}^*(\theta_0, \theta, \phi)\mu_0\mu \quad (5)$$

where μ_0 and μ are cosine of solar zenith angle and cosine of viewing zenith angle, respectively. The surface reflectance ratio k was calculated as the slope of the linear fitting between $\rho_{443}^*(\theta_0, \theta, \phi)\mu_0\mu$ and $F_{443}(\theta_0)T_{443}(\theta)\rho_{680}^*(\theta_0, \theta, \phi)\mu_0\mu$. Drury et al. (2008) and Wang et al. (2010) calculated the one-way transmittance $F_{\lambda}(\theta_0)$ and $T_{\lambda}(\theta)$ separately. We made some improvements by calculating the two-way

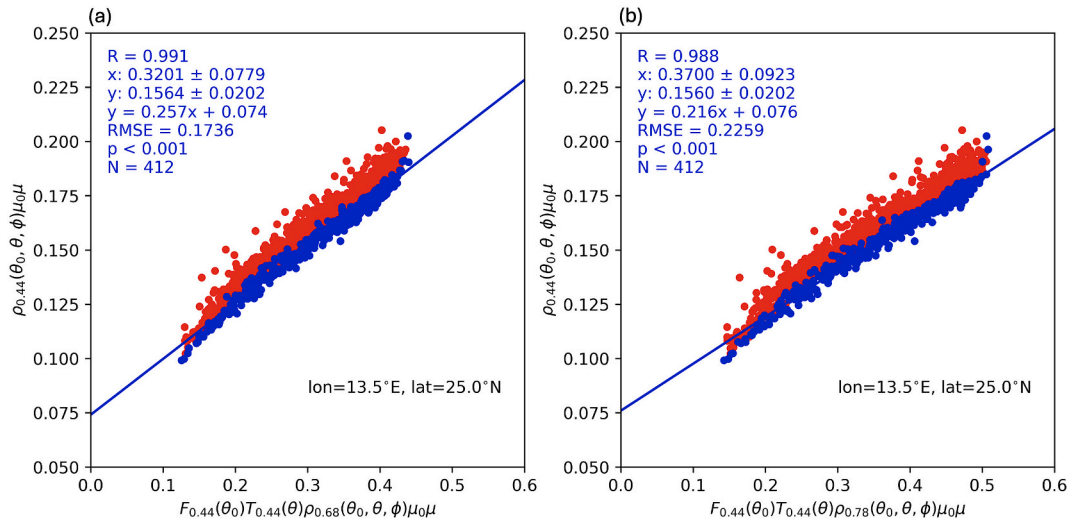


Fig. 5. Scatter plot of scaled EPIC TOA reflectance at $0.44 \mu\text{m}$ ($\rho_{443}^*(\theta_0, \theta, \phi)\mu_0\mu$) versus (a) $0.68 \mu\text{m}$ ($F_{443}(\theta_0)T_{443}(\theta)\rho_{680}^*(\theta_0, \theta, \phi)\mu_0\mu$) and (b) $0.78 \mu\text{m}$ ($F_{443}(\theta_0)T_{443}(\theta)\rho_{780}^*(\theta_0, \theta, \phi)\mu_0\mu$) for one grid box (longitude = 13.5°E , latitude = 25.0°N) for the summer season. The red and blue dots together represent all samples, while the blue dots identify the subset that constitutes the lower envelope of pairs, which was used in the linear regression to calculate the surface reflectance ratio k . (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

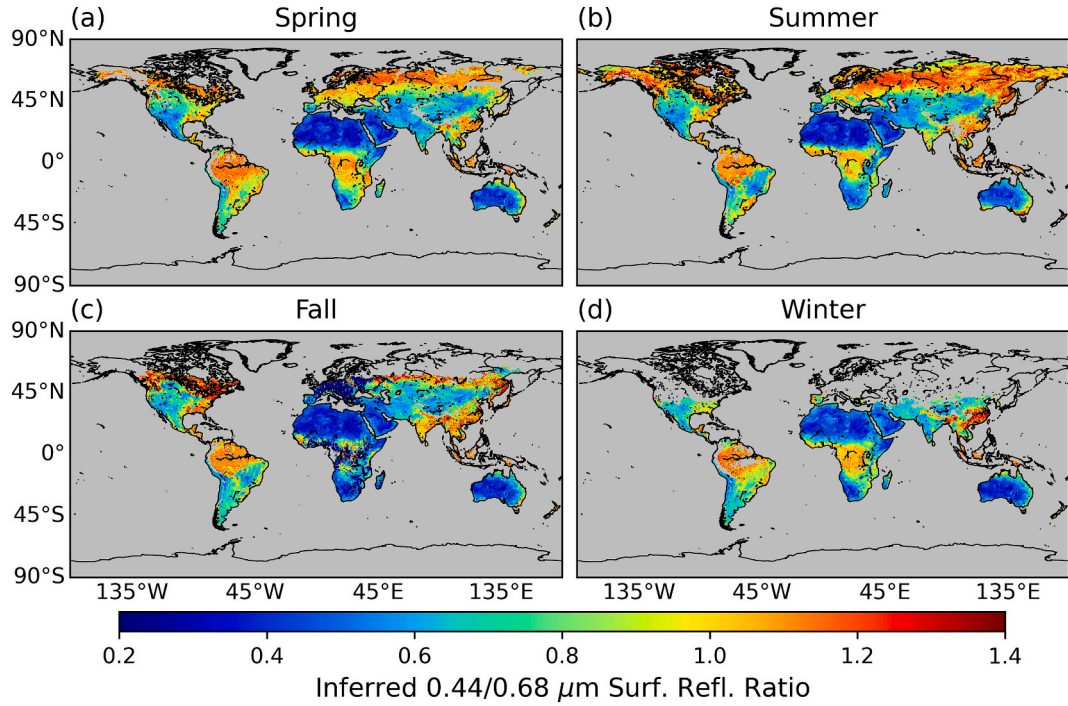


Fig. 6. Global map of inferred surface reflectance ratio of 443 nm to 680 nm for (a) spring, (b) summer, (c) fall and (d) winter.

transmittance $F_{\lambda}(\theta_0)T_{\lambda}(\theta)$ to account for the multiple scattering and interactions between atmosphere and surface. Assuming there is no aerosol and $s_{\lambda} = 0$, from Eq. (2) we have

$$\rho_{\lambda}^*(\theta_0, \theta, \phi) = \rho_{\lambda}^a(\theta_0, \theta, \phi) + F_{\lambda}(\theta_0)T_{\lambda}(\theta)\rho_{\lambda}^s(\theta_0, \theta, \phi) \quad (6)$$

$$F_{\lambda}(\theta_0)T_{\lambda}(\theta) = \frac{\rho_{\lambda}^*(\theta_0, \theta, \phi) - \rho_{\lambda}^a(\theta_0, \theta, \phi)}{\rho_{\lambda}^s(\theta_0, \theta, \phi)} \quad (7)$$

We ran the radiative transfer model UNL-VRM (Wang et al., 2014) to create a lookup table for calculating the two-way transmittance $F_{\lambda}(\theta_0)T_{\lambda}(\theta)$. The entries of the lookup table include solar zenith angle,

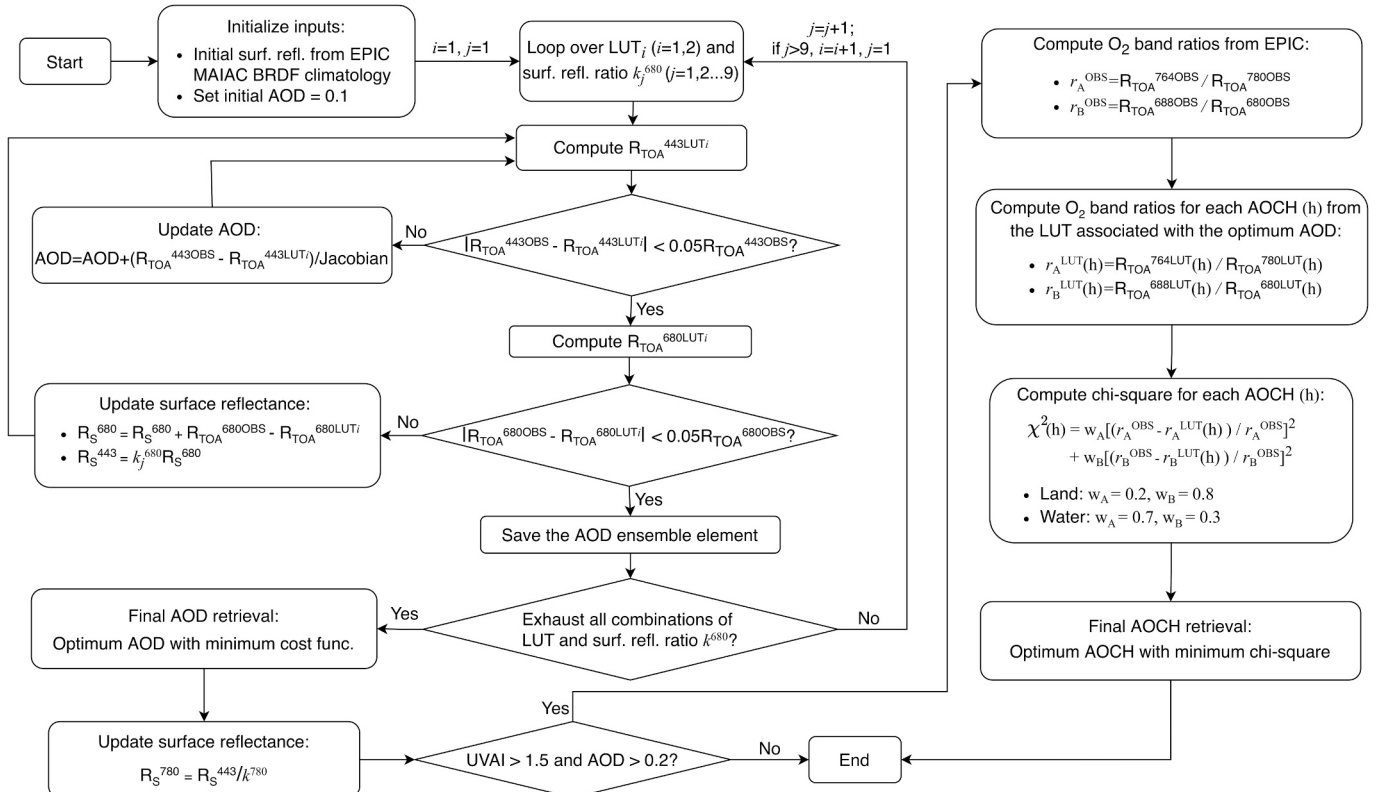


Fig. 7. Workflow of the AOD and AODCH retrieval for EPIC AODCH-v2 algorithm.

viewing zenith angle, relative azimuth angle, surface reflectance and surface pressure. To calculate the two-way transmittance $F_i(\theta_0)T_i(\theta)$ using Eq. (7), the only unknown is $\rho_i^a(\theta_0, \theta, \phi)$. From Eq. (6), we can get $\rho_i^a(\theta_0, \theta, \phi) = \rho_i^s(\theta_0, \theta, \phi)$ when the surface is completely dark, i.e., $\rho_i^s(\theta_0, \theta, \phi) = 0$. In that way, we can calculate the two-way transmittance $F_i(\theta_0)T_i(\theta)$ using the lookup table. The two-way transmittance $F_i(\theta_0)T_i(\theta)$ depends on the surface pressure and surface reflectance. We obtained the surface pressure from MERRA-2 data (Gelaro et al., 2017). The surface reflectance was obtained from EPIC MAIAC BRDF product (Lyapustin et al., 2021). Although EPIC MAIAC BRDF could in principle be used to derive the surface reflectance ratio, they are not adopted here to maintain consistency with the aerosol retrieval framework. Instead, the ratio is estimated directly from EPIC observations using the same radiative transfer assumptions and forward modeling framework as in the aerosol retrieval, rather than relying on an independently derived surface product with its own assumptions and uncertainties.

We derived the global map of surface reflectance ratio with the spatial resolution of $0.5^\circ \times 0.5^\circ$ for each season using three years (2020–2022) of the cloud-screened EPIC data. To form the lower envelope for each grid box and each season, we binned the $F_{443}(\theta_0)T_{443}(\theta)\rho_{680}^s(\theta_0, \theta, \phi)\mu_{0\mu}$ values sequentially into groups with eight samples in each and picked up two samples from each group with the two lowest values of $\rho_{443}^s(\theta_0, \theta, \phi)\mu_{0\mu}$, thereby emphasizing observations under low-AOD conditions with reduced aerosol perturbation. Using the selected subset, the surface reflectance ratio k was then calculated as the slope of the linear regression between $\rho_{443}^s(\theta_0, \theta, \phi)\mu_{0\mu}$ and $F_{443}(\theta_0)T_{443}(\theta)\rho_{680}^s(\theta_0, \theta, \phi)\mu_{0\mu}$. The derivation of the surface reflectance ratio is based on the observations acquired under multiple solar and viewing geometries. The observations with solar zenith angle larger than 55° were excluded to minimize the potential biases associated with the increased atmospheric path length and enhanced multiple-scattering effects. Fig. 5 gives an example of deriving the surface reflectance ratios of 443 nm to 680 nm and 443 nm to 780 nm using the lower envelope technique at one grid box (longitude = 13.5°E , latitude = 25.0°N) for the summer season. This figure illustrates how the lower envelope technique is applied to derive the surface reflectance ratio. The red and blue dots together represent all samples of $\rho_{443}^s(\theta_0, \theta, \phi)\mu_{0\mu}$ versus $F_{443}(\theta_0)T_{443}(\theta)\rho_{680}^s(\theta_0, \theta, \phi)\mu_{0\mu}$ or $F_{443}(\theta_0)T_{443}(\theta)\rho_{780}^s(\theta_0, \theta, \phi)\mu_{0\mu}$. The blue dots denote the subset of samples that constitutes the lower envelope of pairs, while the red dots represent the remaining samples. The lower-envelope samples were used in the linear regression, and the slope of the regression line is derived as the surface reflectance ratio. Fig. 6 displays the global map of inferred surface reflectance ratio of 443 nm to 680 nm for each season. The ratio values are high over vegetated land due to the relatively low surface reflectance at 680 nm. In contrast, the ratio values are low over semi-arid and arid regions because of the high reflectance of bare soil and desert surfaces at 680 nm.

3.4. New scheme for AOD and AOC retrieval

We developed a new scheme for the retrieval of AOD and AOC constrained by the surface reflectance ratio in EPIC AOC-v2 algorithm. Fig. 7 displays the workflow of the new retrieval scheme. We allow the surface reflectance ratio varying by $\pm 10\%$ in the retrieval algorithm to account for the uncertainty of the surface reflectance ratio we derived. Nine scaling factors are applied to the derived surface reflectance ratio: $1, 1 \pm 0.02, 1 \pm 0.04, 1 \pm 0.07$ and 1 ± 0.10 . The choice of nine scaling factors reflects a balance between adequately resolving physically plausible variability and maintaining computational efficiency. Two smoke aerosol models (Section 3.2) and nine alternative surface reflectance ratios are selected by the algorithm one by one and the final AOD retrieval is the optimal retrieval that minimizes the cost function among the AOD ensemble comprising total 18 possible combinations. The cost

function is defined as $\sum_i w_i \left(\frac{R_{\text{TOA}}^{\text{OBS}} - R_{\text{TOA}}^{\text{LUT}}}{R_{\text{TOA}}^{\text{OBS}}} \right)^2$, where i is the index for EPIC

channels at 443 nm, 551 nm and 680 nm. The weighting coefficients w_i for the three bands are 1.0, 0.5 and 1.0, respectively. Only the ensemble element achieving radiative closure at both 443 nm and 680 nm are considered. The radiative closure means the difference of TOA reflectance between lookup table and EPIC measurements is less than 5%. The AOC is finally retrieved using O₂ A and B bands with a least chi-square fitting procedure based on the derived surface reflectance and AOD. While 680 nm AOD serves as the fundamental retrieval and validation anchor, the final EPIC AOC-v2 product dynamically outputs multi-wavelength AODs at 443, 551, 680, and 780 nm, computed using model-specific Ångström exponents to facilitate broader user applications and cross-dataset intercomparisons. AOD retrieval is performed for all aerosol types, whereas the AOC is only retrieved for absorbing aerosols with AOD > 0.2 and UVAI > 1.5. UVAI has been widely used to identify absorbing aerosols with certain threshold (Herman et al., 1997; Kayetha et al., 2022; Lu et al., 2021; Torres et al., 2013). Previous studies have applied UVAI thresholds of 0.8–1.0 to detect absorbing aerosols (Lu et al., 2021; Torres et al., 2013). We additionally applied an AOD threshold to ensure sufficient aerosol loading and retrieval sensitivity. Therefore, the UVAI > 1.5 criterion was adopted as a relatively stricter threshold to identify sufficiently absorbing aerosol scenes. The surface reflectance values at O₂ absorption bands are assumed to be equal to that of continuum bands, i.e., $R_s^{688} = R_s^{680}$, $R_s^{764} = R_s^{780}$.

The retrieval exploits the different spectral sensitivities of TOA reflectance to aerosols and surface reflection. The 443 nm channel is mainly sensitive to aerosol scattering and is therefore used to constrain AOD, while the 680 nm channel provides a stronger constraint on surface reflectance. In addition, the oxygen absorption bands contain information on aerosol layer altitude through regulating the photon path length within the atmosphere, which forms the basis for AOC retrieval. The detailed steps for the optimization of retrievals are as follows. (1) Get the initial surface reflectance from EPIC MAIAC BRDF climatology and set the initial AOD as 0.1. (2) Start or continue the loop by selecting one aerosol model and 443 nm/680 nm surface reflectance ratio k_i^{680} . (3) Compute the TOA reflectance at 443 nm $R_{\text{TOA}}^{443\text{LUT}}$ from lookup table based on the current AOD retrieval and surface reflectance. (4) If $|R_{\text{TOA}}^{443\text{LUT}} - R_{\text{TOA}}^{443\text{OBS}}| < 0.05R_{\text{TOA}}^{443\text{OBS}}$, go to step (6). Otherwise update the retrieved AOD: $\text{AOD} = \text{AOD} + \frac{(R_{\text{TOA}}^{443\text{OBS}} - R_{\text{TOA}}^{443\text{LUT}})}{J}$, where J is the Jacobian of AOD calculated by UNL-VRM. (5) Repeat steps (3) and (4) until $|R_{\text{TOA}}^{443\text{LUT}} - R_{\text{TOA}}^{443\text{OBS}}| < 0.05R_{\text{TOA}}^{443\text{OBS}}$. (6) Compute the TOA reflectance at 680 nm $R_{\text{TOA}}^{680\text{LUT}}$ from the lookup table based on the current AOD retrieval and surface reflectance. (7) If $|R_{\text{TOA}}^{680\text{LUT}} - R_{\text{TOA}}^{680\text{OBS}}| < 0.05R_{\text{TOA}}^{680\text{OBS}}$, go to step (9). Otherwise update the surface reflectance: $R_s^{680} = R_s^{680} + R_{\text{TOA}}^{680\text{OBS}} - R_{\text{TOA}}^{680\text{LUT}}$, $R_s^{443} = k_i^{680}R_s^{680}$. (8) Repeat steps (3)–(7) until $|R_{\text{TOA}}^{680\text{LUT}} - R_{\text{TOA}}^{680\text{OBS}}| < 0.05R_{\text{TOA}}^{680\text{OBS}}$. (9) Save the AOD ensemble element. (10) If all combinations of alternative aerosol models and surface reflectance ratio are exhausted, output the optimum AOD with the minimum cost function as the final retrieval. Otherwise go to step (2). (11) Update the surface reflectance at 780 nm based on the surface reflectance ratios: $R_s^{780} = \frac{R_s^{443}}{k_{780}^{443}}$. (12) If UVAI > 1.5 and AOD > 0.2, go to step (13). Otherwise, terminate the algorithm. (13) Compute the O₂ absorption band ratios $r_A^{\text{OBS}} = \frac{R_{\text{TOA}}^{764\text{OBS}}}{R_{\text{TOA}}^{680\text{OBS}}}$ and $r_B^{\text{OBS}} = \frac{R_{\text{TOA}}^{688\text{OBS}}}{R_{\text{TOA}}^{680\text{OBS}}}$ from EPIC measurements. (14) Compute the O₂ absorption band ratios $r_A^{\text{LUT}} = \frac{R_{\text{TOA}}^{764\text{LUT}}}{R_{\text{TOA}}^{680\text{LUT}}}$ and $r_B^{\text{LUT}} = \frac{R_{\text{TOA}}^{688\text{LUT}}}{R_{\text{TOA}}^{680\text{LUT}}}$ for each AOC value from the lookup table associated with the optimum AOD retrieval. (15) Compute the chi-square for each AOC value: $\chi^2 = w_A \left(\frac{r_A^{\text{OBS}} - r_A^{\text{LUT}}}{r_A^{\text{OBS}}} \right)^2 + w_B \left(\frac{r_B^{\text{OBS}} - r_B^{\text{LUT}}}{r_B^{\text{OBS}}} \right)^2$, where the weighting coefficients w_A and w_B depend on the surface type. For land surface, $w_A = 0.2, w_B = 0.8$. For water surface, $w_A = 0.7, w_B =$

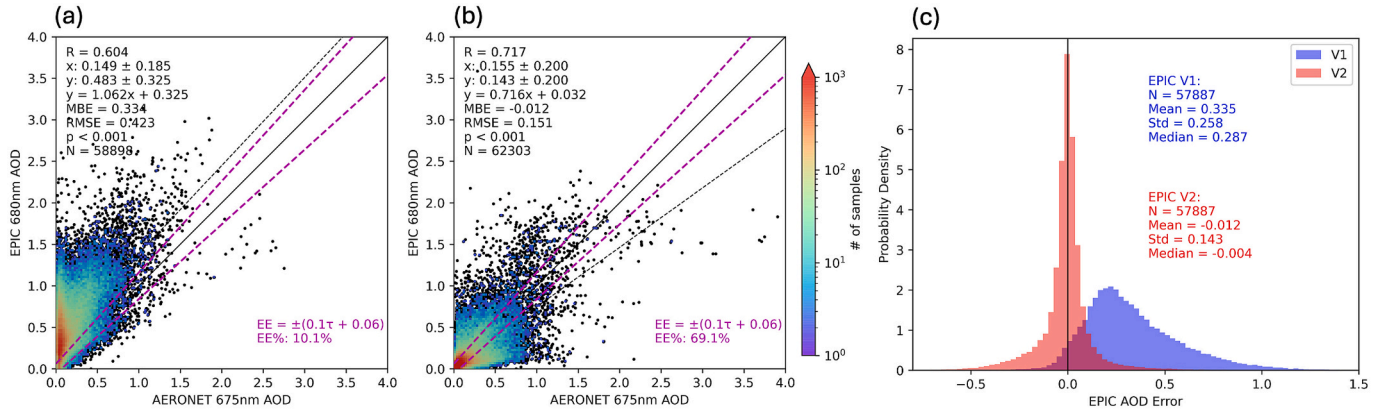


Fig. 8. Comparisons of global AOD retrievals between EPIC and AERONET for 2021 for (a) ACOCH-v1 algorithm, (b) ACOCH-v2 algorithm and (c) the corresponding normalized histograms of EPIC AOD retrieval errors (EPIC minus AERONET). The pink dashed lines in (a) and (b) denote the error envelope, which is defined as $\pm (10\% \text{ AOD} + 0.06)$. The color scheme in (a) and (b) encodes the number of samples with the legend on the right of panel (b). The vertical black line in (c) indicates zero AOD error. The statistics shown in (c) are based on paired ACOCH-v1 and ACOCH-v2 retrievals matched to the same AERONET observations. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

0.3. (16) Output the optimum ACOCH with the minimum chi-square as the final retrieval.

Aerosol type is assigned according to the geographic location of the retrieval pixel. Pixels within 72°E - 135°E and 30°N - 50°N are assigned the East Asian dust model, while pixels within 60°W - 30°E and 5°N - 35°N are assigned the Saharan dust model. All remaining pixels are treated as smoke aerosols. For dust cases over Saharan region and East Asia, only one dust aerosol model is applied for each region. The Saharan dust and East Asia dust aerosol models are adopted from [Chen et al. \(2021\)](#) and [Lu et al. \(2023b\)](#), respectively. The detailed aerosol optical properties are fully described in these publications. Although dust emissions from North American arid and semi-arid regions can occur, they are generally episodic, spatially heterogeneous, and limited in occurrence within the EPIC absorbing aerosol samples ([Hennen et al., 2022](#); [Kandakji et al., 2020](#)). Therefore, dust over North America is not treated as a separate aerosol optical regime in the current retrieval framework, and such cases are included in the smoke category as a practical simplification. Future work may investigate the feasibility of observation-based aerosol type

discrimination using EPIC spectral measurements and ancillary information.

4. Evaluations of EPIC ACOCH-v2 product

4.1. Evaluation of EPIC AOD

AOD is an intermediate variable in the EPIC ACOCH retrieval and is evaluated here in terms of overall performance. [Fig. 8](#) displays the evaluations of the global EPIC AOD retrievals from both the ACOCH-v1 and ACOCH-v2 algorithms against AERONET data for the year 2021. The AERONET-based validation includes both continental sites and a limited number of island or coastal sites. The collocation strategy is that the EPIC pixels within 50 km of AERONET sites and AERONET measurements within 30 min of EPIC overpass are used in the comparison following [Lyapustin et al. \(2021\)](#). The AOD retrievals from ACOCH-v2 algorithm feature a better agreement with AERONET AOD than those of the ACOCH-v1 algorithm. The correlation coefficient increased from

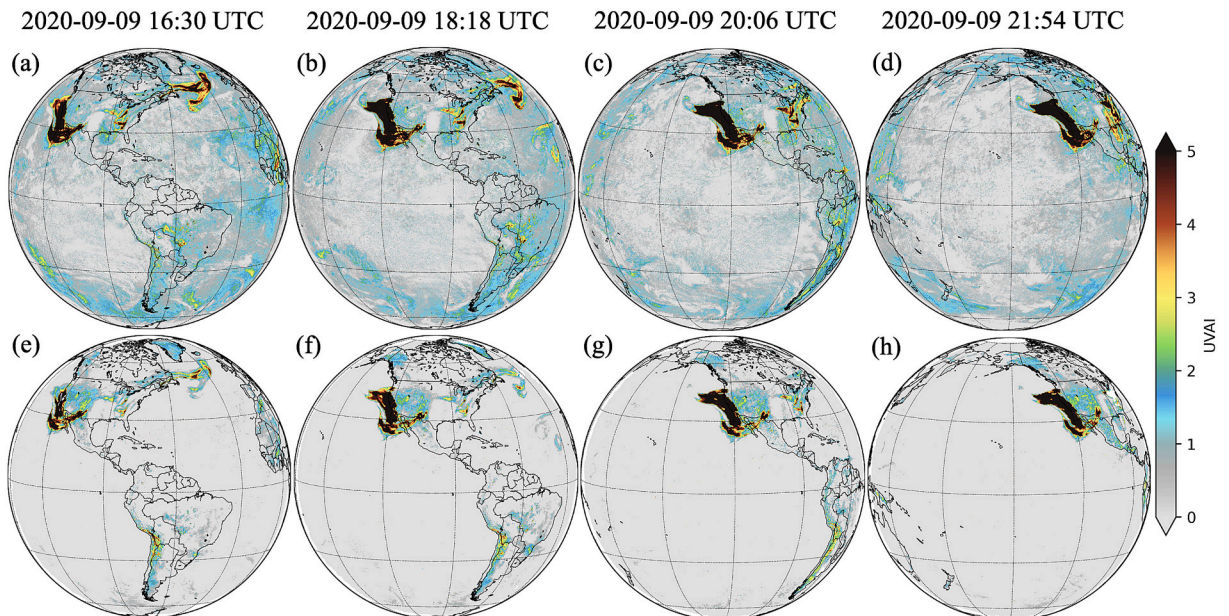


Fig. 9. Comparison of UVAI for the heavy smoke case on Sep. 9, 2020, between (a-d) EPICAERUV and (e-h) EPIC ACOCH-v2 algorithms.

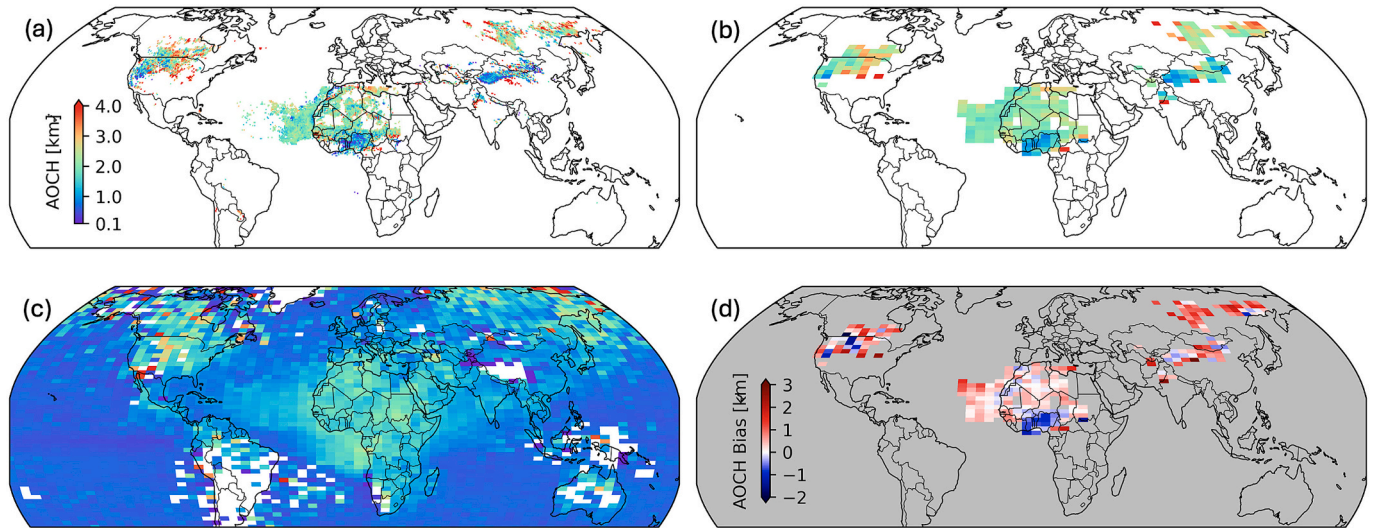


Fig. 10. Comparison of yearly average AODH in 2021 from (a) EPIC AODH-v2 algorithm with the spatial resolution of $0.5^\circ \times 0.5^\circ$, (b) aggregated EPIC AODH with the resolution of $2^\circ \times 5^\circ$ and (c) CALIOP level 3 product with the resolution of $2^\circ \times 5^\circ$. Panel (d) shows the difference between (b) and (c).

0.604 to 0.717, and the root mean square error (RMSE) reduced from 0.423 to 0.151. We define an uncertainty envelope as $\pm (10\% \text{ AOD} + 0.06)$ for the EPIC AOD retrievals, which is comparable in magnitude to the uncertainty of MODIS Collection 6 Dark Target AOD product (Levy et al., 2013), i.e., $\pm (15\% \text{ AOD} + 0.05)$ over land and $(+ (10\% \text{ AOD} + 0.04), - (10\% \text{ AOD} + 0.02))$ over water. 69.1% of AOD retrievals from AODH-v2 algorithm fall within this uncertainty envelope, which is approximately the range of mean plus or minus one standard deviation assuming a normal distribution, while only 10.1% of retrievals from AODH-v1 algorithm fall within the uncertainty envelope due to the significant positive bias with the mean bias error of 0.334. The intercepts of the linear regressions decreased from 0.325 to 0.032, indicating a better characterization of surface reflectance with the constrain of surface reflectance ratio.

This improvement is further illustrated by the normalized histograms of the EPIC AOD retrieval errors (EPIC minus AERONET) for both AODH-v1 and AODH-v2 (Fig. 8(c)), which are derived from paired AODH-v1 and AODH-v2 retrievals matched to the same AERONET observations. The AOD error distribution from AODH-v2 is centered near zero, with the mean error reduced from 0.335 to -0.012 and the median error reduced from 0.287 to -0.004 . In addition, the standard deviation of the retrieval errors decreased substantially from 0.258 to 0.143, indicating a marked reduction in both systematic bias and random error. The much narrower and more symmetric error distribution demonstrates that the AODH-v2 algorithm provides significantly more accurate and consistent AOD retrievals than the AODH-v1 algorithm. To further quantify the significance of the improvement, we performed a paired *t*-test on the absolute AOD retrieval errors of AODH-v1 and AODH-v2 using the same collocated samples. The results indicate that the reduction in absolute retrieval error is statistically significant ($p < 0.001$).

4.2. Comparison of EPIC UVAI

The EPIC AODH-v2 algorithm calculates UVAI from two UV bands at 340 nm and 388 nm following Ahn et al. (2021). We compared the UVAI calculations from EPICAERUV product and AODH-v2 algorithm for the heavy smoke case on Sep. 9, 2020 (Fig. 9). The dense smoke plumes were transported from Western US coast to the ocean, and the strong signals are well captured by both products. However, false alarms occur frequently with UVAI larger than 1 from the EPICAERUV product under high solar and viewing zenith angles at the edge of the EPIC FOR. In contrast, the EPIC AODH-v2 algorithm produces much cleaner UVAI signals at the edges. This improvement stems entirely from the

treatment of the Earth sphericity in the forward radiative transfer simulation. While the EPICAERUV algorithm suffers from substantial errors at extreme viewing geometries due to standard radiative transfer approximations (Ahn et al., 2021), the radiative transfer calculation in this study is conducted by UNL-VRM, which utilizes a highly rigorous two-way pseudo-spherical correction (Spurr, 2008; Spurr, 2006; Wang et al., 2014). Unlike standard pseudo-spherical models that only correct the incoming solar beam, UNL-VRM applies exact spherical shell geometry along both the solar illumination path and the slanted sensor line-of-sight path. By integrating local scattering source functions along the actual curved viewing trajectory, UNL-VRM well reproduces the complex pure-Rayleigh scattering and polarization backgrounds at high viewing and solar zenith angles at the edge of the EPIC FOR. Consequently, the simulated pure-Rayleigh baseline is more consistent with actual EPIC observations at the edge of the EPIC FOR, resetting the UVAI residual back to approximately zero over clean areas and successfully eliminating the geometrically induced false alarms.

4.3. Evaluation of EPIC AODH

We computed and compared the yearly average AODH in 2021 from EPIC AODH-v2 algorithm and CALIOP level 3 product (Fig. 10). The CALIOP AODH is defined as the optical depth weighted height from the CALIOP aerosol extinction profiles by Eq. (1) (Lu et al., 2023a). By definition, the extinction peak height from EPIC AODH retrievals can be different from the AOD weighted height from CALIOP by up to around 0.8 km for the same aerosol extinction profile, especially for the cases with CALIOP AODH lower than 4 km (Kim et al., 2025). To compensate the difference in the definitions of AODH for EPIC and CALIOP, we converted EPIC retrievals into AOD weighted height for all the following comparisons. CALIOP AODH values were converted from height above sea level to height above the local surface by subtracting the corresponding surface elevation, to ensure consistency with the EPIC AODH definition. To align with the observation time of CALIOP, the calculation of yearly average EPIC AODH only includes the EPIC data within the longitude range where the local time differs from the CALIOP overpass time by no more than one hour for each EPIC granule. The EPIC AODH retrievals focus on the absorbing aerosols, excluding data samples with UVAI lower than 1.5 and AOD lower than 0.2. The yearly average EPIC AODH is first calculated at the spatial resolution of $0.5^\circ \times 0.5^\circ$, then we also aggregated the EPIC AODH to a coarser resolution of $2^\circ \times 5^\circ$ to match that of CALIOP level 3 data.

As shown in Fig. 10, the EPIC yearly average AODH well capture the

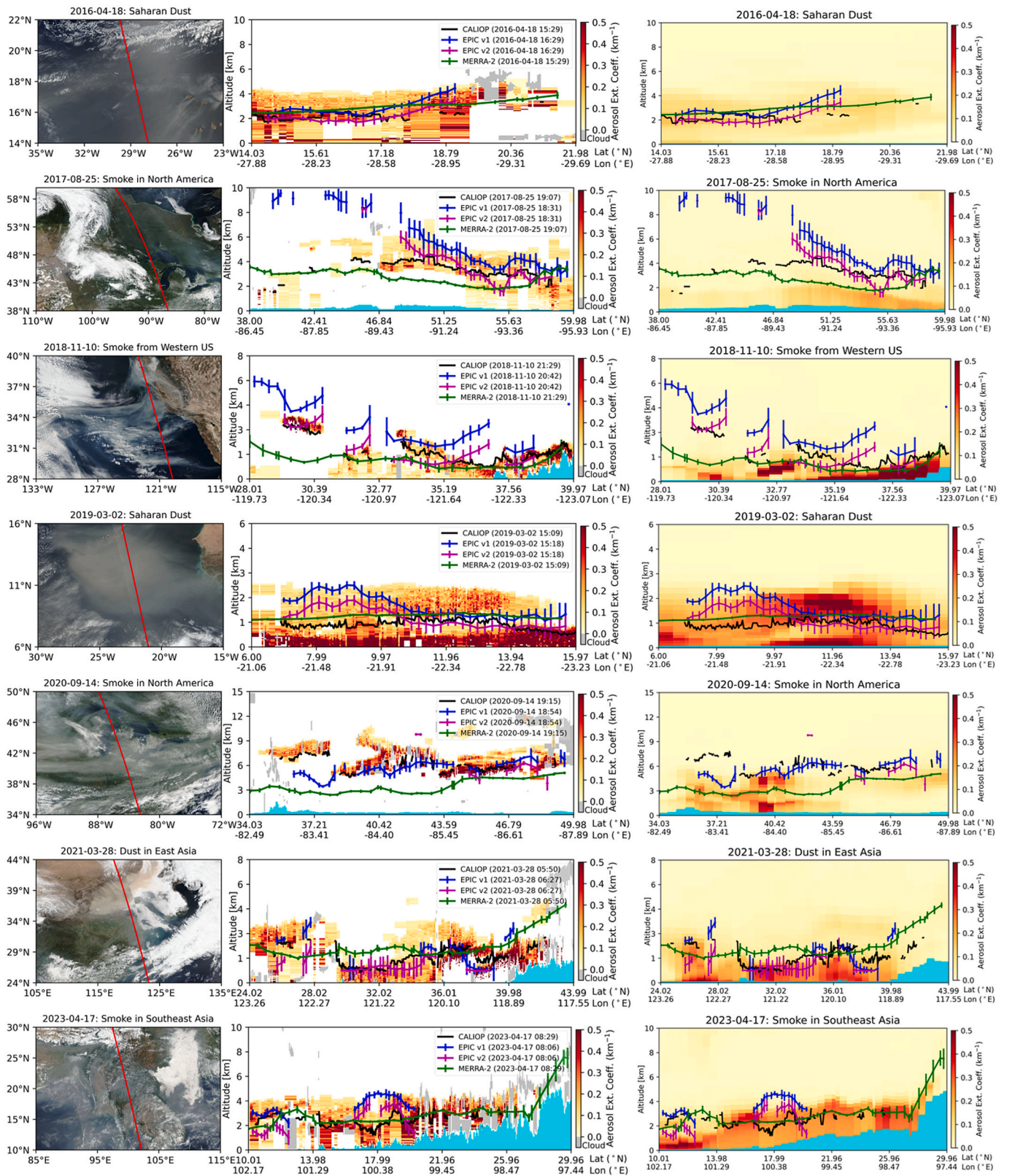


Fig. 11. Comparison of EPIC AOC and MERRA-2 AOC against CALIOP AOC for the seven selected cases. The left panels display the true color images from VIIRS/Suomi NPP with the red line marking the CALIOP tracks. The middle panels are the curtain plot of the CALIOP aerosol extinction profiles. The CALIOP AOC are represented by black lines, and EPIC AOC from the AOC-v1 and AOC-v2 algorithms are marked by blue and pink lines, respectively. MERRA-2 AOC is denoted by green lines. The cyan shading represents the Earth surface. The right panels are the corresponding curtain plots of MERRA-2 aerosol extinction profiles with the same AOC curves as in middle panels. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

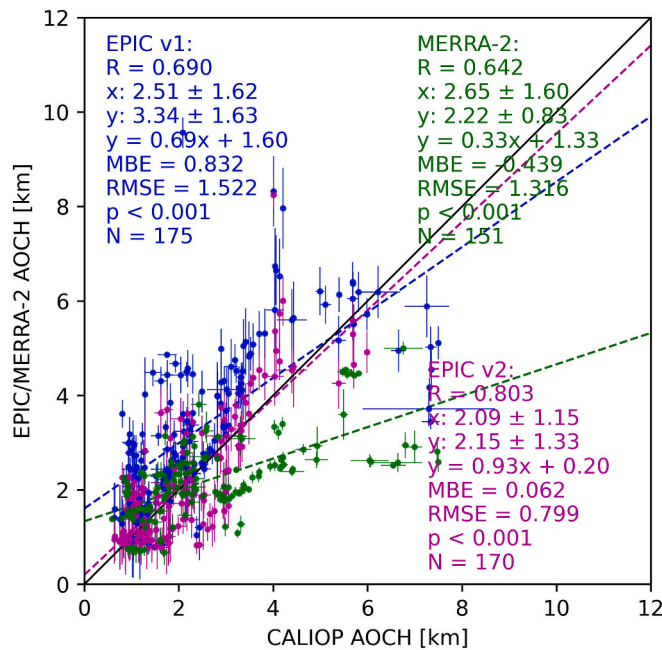


Fig. 12. Scatter plot of EPIC ACH and MERRA-2 ACH against CALIOP ACH for the seven selected cases shown in Fig. 11 with blue color representing ACH-v1 algorithm, pink color representing ACH-v2 algorithm and green color representing MERRA-2. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

spatial pattern of the absorbing aerosol layer height in CALIOP map for North American smoke, Saharan dust and Asian dust. While the EPIC ACH bias exhibits an overall positive tendency, the differences remain within ± 1 km over most regions. Most EPIC-retrieved absorbing aerosol cases are located over land, except for Saharan dust transport over the North Atlantic. In particular, the retrieved EPIC ACH for Saharan dust transport exhibits a smooth and physically consistent transition from source regions over land to downwind oceanic regions without noticeable discontinuity across the coastline. Therefore, the ACH evaluations presented below include collocations over both land and ocean surfaces. The spatial gaps in Fig. 10 are mainly caused by the physical requirements and quality control constraints. The ACH retrieval is only performed for absorbing aerosols with sufficient aerosol loading to

ensure sufficient retrieval sensitivity. Therefore, regions with persistently low AOD or scattering aerosol types, such as Europe and South China, exhibit limited retrieval coverage. Persistent cloud cover in tropical regions associated with the Intertropical Convergence Zone (ITCZ) such as the Amazon Basin, central Africa and Southeast Asia, further reduces valid observations (King et al., 2013; Rossow and Schiffer, 1999). Additional data gaps arise from retrieval quality control and requirement of sufficient valid samples for constructing annual mean values.

We selected seven smoke or dust cases over North America, Saharan region and East Asia in the period of 2016–2023 for the further evaluation of EPIC ACH retrievals. These cases were selected because they were also presented in our previous studies (Chen et al., 2021; Kim et al., 2025; Lu et al., 2021; Xu et al., 2019; Xu et al., 2017), therefore, the evaluation of EPIC ACH-v2 can be made in the context of other algorithms. Fig. 11 shows the true color images from the VIIRS/Suomi NPP for the selected cases, together with the comparisons of EPIC ACH retrieved from the ACH-v1 and ACH-v2 algorithms and MERRA-2 ACH against the CALIOP ACH. Again, the MERRA-2 ACH and CALIOP ACH are defined as the optical depth weighted height from MERRA-2 and CALIOP level 2 aerosol extinction profiles (Lu et al., 2023a). The MERRA-2 ACH is included here to provide additional context for evaluating the performance of the EPIC ACH retrievals relative to a state-of-the-art model-based aerosol product. Fig. 12 is the scatter plot of EPIC ACH from both versions and MERRA-2 ACH against CALIOP ACH for the seven selected cases. The EPIC ACH retrievals from ACH-v2 algorithm exhibit improved consistency with CALIOP measurements compared to ACH-v1 algorithm. The overestimation of ACH by EPIC ACH-v1 algorithm is significantly mitigated by the ACH-v2 algorithm, with the mean bias error reduced from 0.832 km to 0.062 km. The R value increased from 0.690 to 0.803 and RMSE decreased from 1.522 km to 0.799 km. Figs. 11 and 12 show that the MERRA-2 ACH agree well with CALIOP observations for the aerosol layers lower than 3 km, such as the Saharan dust on April 18, 2016, and the smoke in Southeast Asia on April 17, 2023. However, when the aerosol plumes rise above 3 km, MERRA-2 ACH tends to significantly underestimate the aerosol layer heights, as illustrated by the two smoke cases in North America on August 25, 2017, and September 14, 2020. The slope of the linear regression between MERRA-2 ACH and CALIOP ACH is as low as 0.33, and the mean bias error is -0.439 km. This result demonstrates the advantage of the EPIC ACH retrievals over the MERRA-2 dataset, especially for the elevated aerosol plumes above the boundary layer. It highlights the potential of EPIC

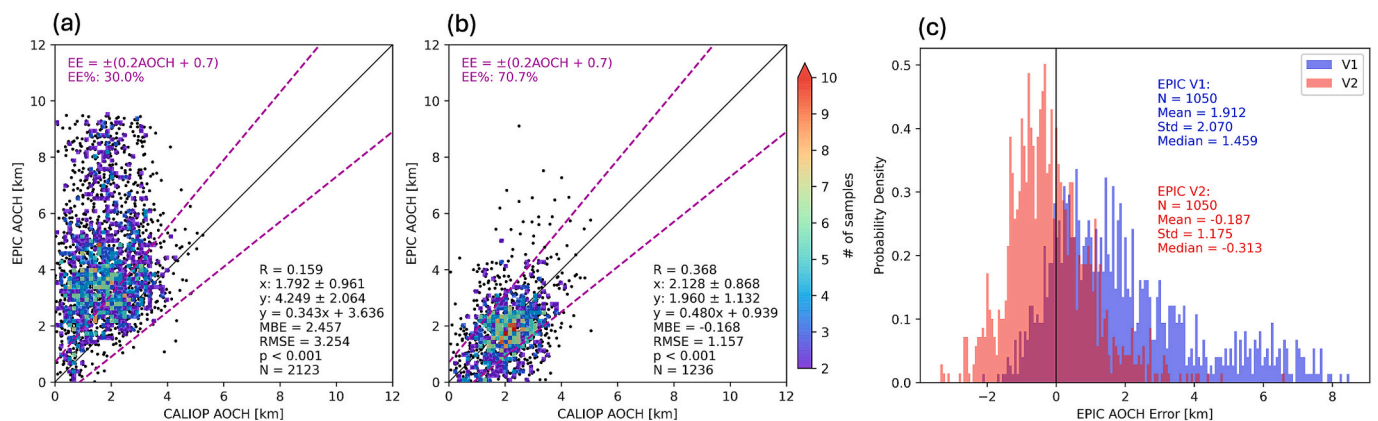


Fig. 13. Scatter plot of global ACH for the year 2021 between CALIOP and (a) EPIC ACH-v1 algorithm, (b) EPIC ACH-v2 algorithm and (c) the corresponding normalized histograms of EPIC ACH retrieval errors (EPIC minus CALIOP). The pink dashed lines in (a) and (b) denote the error envelope, which is defined as $\pm (20\% \text{ ACH} + 0.7 \text{ km})$. The color scheme in (a) and (b) encodes the number of samples with the legend on the right of panel (b). Note, the AOD in v1 algorithm is significantly overestimated (Fig. 8). Therefore, there are more cases with AOD > 0.2 in v1 algorithm than v2, thus generating more ACH retrievals from v1 algorithm. The vertical black line in (c) indicates the zero ACH error. The statistics shown in (c) are based on paired ACH-v1 and ACH-v2 retrievals matched to the same CALIOP observations. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

AOCH to provide valuable observational constraints on aerosol vertical distributions in model and reanalysis systems.

Fig. 13 presents the evaluations of EPIC global AOCCH retrievals for the year 2021 from both AOCCH-v1 and AOCCH-v2 algorithm against CALIOP AOCCH from level 2 Aerosol Profile product. For each set of 19 continuous CALIOP footprint, we identify the EPIC pixel closest to the central CALIOP footprint and compute the mean AOCCH of the surrounding 3×3 EPIC pixels. The spatial resolutions of CALIOP level 2 product and EPIC AOCCH are 5 km and ~ 30 km, respectively. Therefore, the spatial extent of 19 CALIOP footprints is comparable to 3×3 EPIC pixel window. The mean EPIC AOCCH from the 3×3 pixels is then compared with the mean AOCCH of the 19 CALIOP footprints, using only EPIC measurements acquired within 1 h of the CALIOP overpass. Fig. 13 indicates the EPIC AOCCH-v2 algorithm dramatically improve the agreement between EPIC AOCCH and CALIOP AOCCH compared with EPIC AOCCH-v1 algorithm. Because the AOD from AOCCH-v1 algorithm is significantly overestimated (Fig. 8), there are more cases with AOD > 0.2 in v1 algorithm than v2, resulting in a larger number of AOCCH retrievals from v1 algorithm. The AOCCH retrievals are biased high, whereas v2 algorithm significantly mitigates the AOCCH overestimation in v1 algorithm through better characterization of surface reflectance, updated smoke aerosol model and enhanced AOD retrievals. This result is consistent with the case studies displayed in Figs. 11 and 12. We defined an uncertainty envelope as $\pm (20\% \text{ AOCCH} + 0.7 \text{ km})$ for EPIC AOCCH retrievals. 70.7% of AOCCH-v2 retrievals fall within this uncertainty envelope, compared with only 30.0% for AOCCH-v1.

The improvement is further demonstrated by the normalized histograms of EPIC AOCCH retrieval errors (EPIC minus CALIOP) for both AOCCH-v1 and AOCCH-v2 (Fig. 13(c)), which are derived from paired AOCCH-v1 and AOCCH-v2 retrievals matched to the same CALIOP observations. The AOCCH-v1 retrievals exhibit a substantial positive bias, with a mean error of 1.912 km and a median error of 1.459 km, whereas the mean and median errors are reduced to -0.187 km and -0.313 km, respectively, for AOCCH-v2. In addition, the standard deviation of the retrieval errors decreases from 2.070 km to 1.175 km, indicating a substantial reduction in both systematic and random errors. The narrower and more symmetric error distribution of AOCCH-v2 further confirms the improved accuracy and consistency of the updated algorithm. A paired *t*-test performed on the absolute AOCCH retrieval errors using the same collocated samples indicates that the improvement from AOCCH-v1 to AOCCH-v2 is statistically significant ($p < 0.001$). The comparison based on the same set of collocated samples confirms that the AOCCH retrieval improvement is associated with algorithmic updates in AOCCH-v2, including improved surface reflectance representation, enhanced AOD retrieval, and updated aerosol optical models.

5. Summary

This paper presents the AOCCH-v2 algorithm to retrieve near-hourly AOD, AOCCH and UVAI from EPIC measurements. The AOD, AOCCH and UVAI are retrieved from blue and red bands (443 and 680 nm), oxygen absorption bands (688 and 764 nm) and two UV channels (340 and 388 nm), respectively. Compared to the AOCCH-v1 algorithm, the AOCCH-v2 algorithm includes the following modifications: (a) The cloud mask scheme was updated to reduce cloud over-screening over bright surfaces. (b) A new smoke aerosol model was added for large AOD conditions over North America. (c) A new iterative retrieval scheme was developed to constrain AOD and AOCCH retrievals by the surface reflectance ratios. (d) The UVAI calculation was added to improve retrievals at the edge of the FOR.

We added a new cloud detection test using the ratio of NIR band (780 nm) to visible (VIS) band (443 nm). The logic flow of all the tests in the cloud mask scheme is also redesigned. The misclassification of bright surface as clouds has been significantly mitigated with the updates. The real part refractive index of the smoke aerosol model was updated from 1.550 to 1.459 to generate a new smoke aerosol model for large smoke

AOD scenarios. The original aerosol model generated from the AERONET climatology is used for the background aerosols. We designed a new retrieval algorithm that combines the two smoke aerosol models. The new EPIC AOD and AOCCH retrievals are constrained by the surface reflectance ratios.

We compared the AOD and AOCCH retrievals from both the EPIC AOCCH-v1 and AOCCH-v2 algorithms against collocated AERONET and CALIOP aerosol products. EPIC AOD retrievals from the AOCCH-v2 algorithm displayed a better agreement with AERONET than those from the AOCCH-v1 algorithm, with the linear correlation coefficient (*R*) value increased from 0.604 to 0.717 and RMSE decreased from 0.423 to 0.151. Statistically, 69.1% of AOD retrievals from AOCCH-v2 algorithm fell within the uncertainty envelope of $\pm (10\% \text{ AOD} + 0.06)$. In contrast, only 10.1% of AOD retrievals from the AOCCH-v1 algorithm felled within this uncertainty envelope. The yearly average of AOCCH from the AOCCH-v2 algorithm well captured the spatial distribution of the absorbing aerosol layer height in the CALIOP map for smoke over North America and dust aerosols over Sahara and Asia. The overestimation of AOCCH by EPIC AOCCH-v1 algorithm is significantly mitigated with the AOCCH-v2 algorithm: 70.7% of AOCCH-v2 retrievals fall within the uncertainty envelope of $\pm (20\% \text{ AOCCH} + 0.7 \text{ km})$, compared with the counterpart of 30.0% from the AOCCH-v1. This result suggests the better characterization of surface reflectance, the enhanced AOD retrievals and the updated smoke aerosol model effectively reduced uncertainties in the EPIC AOCCH retrievals. Besides, the comparison of EPIC AOCCH versus MERRA-2 AOCCH demonstrates the advantage of the EPIC retrievals over the MERRA-2 dataset, which tends to underestimate the altitude of elevated aerosol plumes above the boundary layer. A systematic comparison of EPIC AOCCH with other passive ALH retrieval algorithms will be conducted in future work. Finally, the UVAI calculation from EPIC AOCCH-v2 algorithm accounts for the Earth curvature effects more realistically than the EPICAERUV product.

CRedit authorship contribution statement

Zhendong Lu: Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Writing – review & editing, Writing – original draft. **Jun Wang:** Supervision, Resources, Project administration, Methodology, Funding acquisition, Conceptualization, Writing – review & editing. **Xi Chen:** Supervision, Software, Formal analysis, Writing – review & editing. **Meng Zhou:** Supervision, Formal analysis. **Xiaoguang Xu:** Software, Writing – review & editing. **Yeonsu Park:** Data curation. **Hyerim Kim:** Software.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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