Detecting layer height of smoke aerosols over vegetated land and water surfaces via oxygen absorption bands: Hourly results from EPIC/DSCOVR satellite in deep space

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Abstract. We present an algorithm for retrieving aerosol layer height (ALH) and aerosol optical depth (AOD) for smoke over vegetated land and water surfaces from measurements of the Earth Polychromatic Imaging Camera (EPIC) onboard the Deep Space Climate Observatory (DSCOVR). The algorithm uses earth-reflected radiances in six EPIC bands in visible and near-infrared and incorporates flexible spectral fittings that account for specifics of land and water surface reflectivity. The
20 fitting procedure first determines AOD using EPIC atmospheric window bands (443 nm, 551 nm, 680nm, and 780 nm), then uses oxygen (O_2) A and B bands (688 nm and 764 nm) to derive the ALH that represents an optical centroid altitude. ALH retrieval over vegetated surface primarily takes advantage of the measurements in the O_2 B band. We applied the algorithm to EPIC observations of several biomass burning events over United State and Canada in August 2017. We found the algorithm can well capture AOD and ALH multiple times daily over water and vegetated land surface. Validations are
25 performed against aerosol extinction profile detected by the Cloud-Aerosol Lidar with Orthogonal Polarization (CALIOP) and AOD observed at nine Aerosol Robotic Network (AERONET) sites, showing, in average, an error of 0.58 km and a bias of -0.13 km in retrieved ALH and an error of 0.05 and a bias of 0.03 in retrieved AOD. Additionally, we show that the aerosol height information retrieved by the present algorithm can potentially benefit the retrieval of aerosol properties from the EPIC's ultraviolet (UV) bands.

1 Introduction

30 Aerosol vertical distribution is an important but poorly constrained variable that strongly influences how aerosol particles affect earth's energy budget. In particular, absorption of solar radiation by smoke and dust particles can result in diabatic heating, alter atmospheric stability, and affect cloud formation and life cycle. These effects depend critically on the altitude of aerosol layers (Babu et al., 2011;Koch and Del Genio, 2010;Satheesh et al., 2008;Wendisch et al., 2008;Ge et al., 2014).
35 Consequently, aerosol profile factors into the magnitude and even the sign of aerosol direct and indirect effects. An accurate representation of aerosol altitude is thus essential for model prediction of weather and climate (Choi and Chung, 2014;Samset et al., 2013). The thermal signature of dust in particular can likewise influence the earth longwave budget and through the interference of retrievals of water vapor and temperature, thus influencing measure atmospheric state (Maddy et al., 2012). Additionally, the knowledge of ALH is essential in retrieving aerosol absorption properties in the ultraviolet (UV)

channels (Torres et al., 1998), in retrieving aerosol microphysical properties from multi-angular photopolarimetric measurements (Waquet et al., 2009;Chowdhary et al., 2005), and in the atmospheric correction for ocean color remote sensing (Duforêt et al., 2007).

Despite the importance of aerosol vertical distribution, the simulation of aerosol layer height (ALH) in current climate

5   models is subject to large inter-model variation and uncertainty (Koffi et al., 2012;Kipling et al., 2016). Although the assimilation of space-borne Lidar (e.g., CALIOP, or the Cloud-Aerosol Lidar with Orthogonal Polarization) observations can improve the prediction of vertical allocation (Zhang et al., 2011), a significant challenge remains due to the sparsity of lidar observations over space and time. Therefore, frequent satellite observations of global aerosol vertical distribution based on more abundant observation sources are critically needed.

10   One such source, the recently-launched Deep Space Climate Observatory (DSCOVR) mission, has introduced an unprecedented opportunity to acquire ALH information multiple times daily. Launched on 11 February 2015, the DSCOVR spacecraft flies a Lissajous orbit around the Sun-Earth L_1 Lagrangian point about 1.5 million km from Earth in the direction of the Sun. While its primary payload is the Plasma-Magnetometer that measures solar wind, DSCOVR also carries the Earth Polychromatic Imaging Camera (EPIC) to image the sunlit disk of Earth every $60 - 100$ minutes from its stable L_1 vantage

15   point. EPIC captures its imagery at a 2048-by-2018-pixel resolution, resolving about 8-km pixel resolution at the disk's center. EPIC was equipped with a double wheel filter to sequentially measure Earth-reflected solar radiance in ten narrow bands spanning from UV to near-infrared (NIR) spectrum (Figure 1a), with central wavelengths at 318 nm, 325 nm, 340 nm, 388 nm, 443 nm, 551 nm, 680 nm, 688 nm, 764 nm, and 780 nm (Marshak et al., 2018).

As shown in Figure 1b-c, two of EPIC's bands are located within the oxygen (O_2) "A" and "B" bands (764 nm and 688 nm),

20   each associated with a reference continuum band at 780 nm and 680 nm, respectively. These four bands, offering the spectral contrasts between absorption bands and continuum bands (known as the Differential Optical Absorption Spectroscopic, or DOAS, ratios), were originally designed for determining cloud height (Yang et al., 2013). Recently, Xu et al. (2017) present an algorithm to simultaneously retrieve aerosol optical depth (AOD) and ALH using the EPIC measurements via these four bands and, for the first time, demonstrate EPIC's promising application for determining dust plume height over ocean

25   surfaces during the daytime hours.

The present study, building upon the development of Xu et al. (2017) in determining dust ALH over ocean, extends the algorithm to retrieve ALH from EPIC measurements over land surfaces as well. The new developments in this study includes implementing smoke aerosol optical properties, land surface characterization, and more robust strategies in the procedures of pixel selection and spectral fitting. The augmentation of the Xu et al. (2017) algorithm takes an important

30   additional step towards our goal of providing more frequent global ALH and AOD information for multi-species global aerosol.

The paper is outlined as follows. Section 2 briefly reviews the physical principle for remote sensing of ALH in the O_2 absorption bands and explains the challenges to retrieving ALH over land surfaces, implicating our algorithm development

limited to water and vegetated land surface. Section 3 describes the key elements, procedures, and the assumptions of the updated ALH retrieval algorithm. The ALH retrievals are demonstrated in Section 4, that were applied to smoke events over Canada and the United States in August 2017. Section 5 evaluates the retrieved smoke ALH and AOD from EPIC with aerosol extinction profile measured by CALIOP and AOD measured at AERONET sites. In conclusion, section 6

5   summarizes our findings and discusses potential broader applications of this new ALH information.

2 Remote Sensing Principle and Challenges

The ALH retrieval from EPIC takes advantage of the absorption features of molecular O_2 in the A band at 759 – 771 nm and the B band at 686 – 695 nm. The electronic transitions from the ground state to two excited states of an O_2 molecule, coupled

10   with vibrational-rotational transitions, produce O_2 absorption lines in the A and B bands with distinct spectral variability (Figure 1b-c). As a result, the large variability of atmospheric opacity within the O_2 A and B bands leads to a wide range of penetration depths of solar radiation (Ding et al., 2016). The spectroscopic characteristics in the O_2 bands are related to how the scattering of presented aerosol particles interact with O_2 absorption at different altitudes. Furthermore, since O_2 molecules are well mixed in the atmospheric column, the altitude-dependence of O_2 absorption can provide information on

15   the path length of light scattered by aerosol particles and thus is related to the height of aerosol layers. The premise of this retrieval dates back to Hanel (1961) and Yamamoto and Wark (1961), who estimate cloud top pressure based on the amount of absorption by molecular CO_2 and O_2 above the cloud layer. More recently, a number of satellite sensors have been designed to capture the O_2 absorption feature to provide cloud top height and ALH, among those are GOME, SCIAMACHY, MERIS, POLDER, DSCOVR, and most recently TROPOMI (Xu et al., 2018a and references therein).

20   Figure 2 illustrates the physical principle for sensing of ALH with O_2 absorption spectroscopic approach, which relies on the fact that a scattering aerosol layer can scatter sun light back to space, shortening the path length of a photon traveling in the atmosphere, and thus reduce the chance of a photon being absorbed by O_2 molecules. As a result, an elevated scattering layer enhances the TOA reflectance within the O_2 absorption bands as detected by a satellite. In other words, for a given aerosol layer of fixed AOD placed at different altitudes, the higher the altitude, the larger the TOA reflectance, i.e., $I_H > I_L$ in Figure

25   2. This relationship contrasts to that of the reference continuum band, where the TOA reflectance is not sensitive to vertical location of the aerosol layer but depends only on the column AOD, i.e., $I_H = I_L$ for a given AOD. Based on this principle, the ratio of TOA reflectance between in-band and continuum band, or the DOAS ratio, provides a practical way to infer the ALH (e.g., Dubuisson et al., 2009b;Xu et al., 2017;Duforêt et al., 2007).

To build the links between DOAS ratios and ALH, we simulate TOA reflectance as observed by EPIC measurements with a

30   state-of-the-art Unified Linearized Vector Radiative Transfer Model (UNL-VRTM; described in section 3.5). Figure 3 shows simulations of the relationship between smoke ALH (y axis) and DOAS ratios (x axis) formulated by EPIC channels in O_2 A and B bands for various AOD values and surface reflectance (A_s, indicated by different colors). Those simulations were performed for a typical biomass-burning aerosol model as observed by EPIC at the geometry of $[\theta_0, \theta, \Delta\phi] = [42°, 37°, 165°]$, where θ_0 and θ are solar and viewing zenith angles, and $\Delta\phi$ the relative azimuth angle between the sun and

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the viewer. As seen from Figure 3, the DOAS ratios in general increase with the rise of ALH. Meanwhile, the relationship is strongly dependent on the aerosol loading and surface reflectivity.

The sensitivity of DOAS to ALH is enhanced for lower surface reflectance and larger AOD. Conversely, the sensitivity decreases rapidly for smaller AOD (e.g., AOD = 0.1 in Figure 3a, d) or as A_s increases, a condition where it is difficult to
5   discriminate between the aerosol scattering contribution to TOA reflectance and the contribution from surface. Therefore, it is challenging to obtain ALH information for low aerosol loading conditions and over bright surfaces. This is consistent with findings of many previous information content studies for determining ALH from the O_2 A and B band measurements (Dubuisson et al., 2009b;Ding et al., 2016). Duforêt et al. (2007) show that the centroid altitude of a single aerosol layer over a dark surface can be retrieved from Polarization and Directionality of the Earth's Reflectances (POLDER)
10 measurements with an error of less than 1 km when AOD is over 0.2. Similarly, Dubuisson et al. (2009b) suggest AOD > 0.3 and $A_s < 0.06$ in order to achieve the retrieval accuracy of 0.5 km from POLDER.

With the above retrieval principles and challenges in mind, for our algorithm development we need to determine over what underlying earth surfaces EPIC measurements have sufficient information to allow a practical retrieval of ALH. First and foremost, the surface reflectance must be low enough in one of the O_2 A and B bands to provide unambiguous signal from
15 the aerosol. According to Figure 3, the DOAS-ALH sensitivity becomes substantial when $A_s < 0.1$ in moderate aerosol loading conditions ($\tau_{680} = 0.4$). Hence, $A_s = 0.1$ is set as the upper threshold, above which an ALH retrieval will not be attempted, despite the sensitivity increases in high aerosol loading ($\tau_{680} = 1.0$) for higher A_s.

Figure 4 shows the magnitude of surface reflectance from the ASTER spectral library for typical earth surface types (Baldridge et al., 2009). The water surface is dark, with reflectance lower than 0.03 in both the O_2 A and B bands. Over land,
20 green vegetation is the only surface type that offers a reflectance below 0.1 ($A_s = 0.1$ is indicated by the red dotted line), in the O_2 B band. In fact, A_s in the O_2 A-band is considerably above 0.1 for all land types considered in Figure 4. These findings provide important guidance on the ALH algorithm design. Specifically, EPIC can retrieve ALH only over water and vegetated surfaces. In particular, ALH retrieval over vegetated surface would enlist DOAS ratios in the O_2 B-band. Additionally, retrieval of ALH requires a sufficiently high aerosol loading. We set AOD thresholds for retrieving ALH over
25 both the water and vegetation per the algorithm overview to follow.

3. EPIC Aerosol Layer Height Retrieval Algorithm
3.1 Algorithm overview

Figure 5 illustrates the processing of EPIC data and the ALH retrieval procedure. Briefly, the retrieval algorithm entails the
30 following steps:

1. Calculate TOA reflectance at six EPIC visible and NIR bands (443, 551, 680, 688, 764, and 780 nm) from the calibrated EPIC level 1B digital data.

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2. Identify EPIC pixels that are suitable for aerosol height retrieval. Through various tests, this step screens out pixels having clouds, over-water sun glints, and bright land surfaces, which are performed separately for water and land pixels. Surface pressure comes from MERRA-2 reanalysis data and we determine surface reflectance at EPIC bands using GOME-2 and MODIS surface products.

5   3. Aggregate the EPIC original pixels into a box of 3×3 individual pixels, an area with size of about 24 km at nadir. In many cases, not all pixels within a box are suitable for retrieval (i.e., cloud, glint, and bright land). If the number of available pixels within a box is not less than 4 (of the total of 9), calculate mean values of TOA reflectance, satellite geometries, and surface reflectance of available pixels. Otherwise, do not conduct an aerosol retrieval for the box.

10   4. Invert the aggregated EPIC observations using pre-calculated lookup tables to obtain smoke ALH and AOD. The inversion uses a flexible spectral fitting strategy that considers specific surface type.

While the retrieval procedure is based up on our algorithm of retrieving dust ALH over ocean from the EPIC (Xu et al., 2017), it was upgraded in a few aspects. First, the algorithm extends to retrieve ALH over vegetated land surface. The capability of inferring ALH over vegetation is predicated on the O2 B band, where the surface reflectance is sufficiently low. Accordingly, the new algorithm uses methods separated for land and water surfaces in determining surface reflectance and screening cloud. Second, the algorithm incorporates a smoke aerosol optical model in order to retrieve biomass-burning smoke ALH. Third, rather than aggregating EPIC data from satellite pixels to regular latitude-longitude grids, the new algorithm retrieves over aggregated boxes, each consisting of an array of 3×3 EPIC pixels. This change is based on the consideration that geolocation of EPIC data has made significant improvements in the new version of level 1B data (Geogdzhayev and Marshak, 2018). Lastly, to obtain AOD and ALH the new algorithm employs a flexible spectral fitting strategy by considering the underlying surface reflectivity. In the following procedural subsections, we describe these changes in full detail.

3.2 Obtain EPIC TOA reflectance

25   For this algorithm development, we used the EPIC Level 1B (L1B) Version 02 imagery data, available from NASA's Atmospheric Science Data Center (ASDC) at https://eosweb.larc.nasa.gov (last accessed Nov 26, 2018). Various pre- and post-launch calibrations were applied to the L1B EPIC data. EPIC visible and near-IR (NIR) channels at 443, 551, 680, and 780 nm were cross-calibrated with independent LEO satellite instruments, including the MODIS onboard the Terra and Aqua satellites (Geogdzhayev and Marshak, 2018). The two O_2 absorption channels (688 nm and 764 nm) were calibrated by lunar surface reflectivity with EPIC lunar observations at the time of full moon as seen from the earth (Ohtake et al., 2010). The image data in EPIC L1B products is in digital units of counts/second, that is converted into reflectance for each visible and NIR channel by calibration factors derived by above studies. The calibration factors for all EPIC channels are provided at ASDC online: https://eosweb.larc.nasa.gov/project/dscovr/DSCOVR_EPIC_Calibration_Factors_V02.pdf (last accessed Nov 26, 2018). The top-of-the-atmosphere (TOA) reflectance values are calculated as:

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$$\rho_\lambda = \frac{K(\lambda)C(\lambda)}{\mu_0}, \quad (1)$$

where $C(\lambda)$ is EPIC measured signal in the units of counts/second at the wavelength of λ, $K(\lambda)$ is a calibration factor, and μ_0 is the cosine of solar zenith angle, θ_0. Additionally, pixels that are far from nadir and strongly distorted by the Earth ellipsoid (e.g., view zenith angle $\theta > 70°$ or solar zenith angle $\theta_0 > 70°$) are excluded.

5

3.3 Determine surface albedo and pressure

Past studies show that an accurate ALH retrieval critically depends on the appropriate assumption of surface reflectance (Corradini and Cervino, 2006;Ding et al., 2016;Dubuisson et al., 2009a). As discussed in the preceding section, our retrievals are confined to water and dark vegetated surfaces. Land and water mask information for each EPIC pixel was determined

10   using the GSHHG coastline database (Wessel and Smith, 1996). Following Xu et al. (2017), surface reflectance over water surface was obtained from the GOME-2 surface Lambert-equivalent reflectivity (LER) database (Koelemeijer et al., 2003;Tilstra et al., 2017). GOME-2 LER products contain spectral LER albedo at 21 one-nanometer-wide channels, available globally for each month of the year at 0.25°×0.25° grid spacing (~25 x 25 km cells). From these data, we selected LER albedos at 440, 555, 670, 758, and 780 nm to represent surface reflectance for the nearest EPIC bands.

15   The Moderate-resolution Imaging Spectroradiometer (MODIS) BRDF/Albedo product (MCD43) provides parameters that can be used to determine surface reflectance over land in MODIS's first seven channels (Schaaf et al., 2002;Lucht et al., 2000). Those parameters, including surface bidirectional reflectance distribution function (BRDF) and albedos, were inverted from the atmospherically-corrected (i.e., Rayleigh and aerosol components removed) MODIS reflectance observations from both the Terra and Aqua satellites over a 16-day period. We used black-sky albedo and white-sky albedo

20   compiled in the Level-3 daily Climate Modeling Grid (CMG) Albedo Product (MCD43C3) at a spatial resolution of 0.1°×0.1°. Here, black-sky albedo is the directional hemispherical reflectance if the illumination comes only from the sun at solar noon. White-sky albedo is the bi-hemispherical reflectance under isotropic sky-light illumination. The actual bi-hemispherical reflectance can be computed from white-sky and black-sky albedos via a weighting coefficient that depends primarily on solar angle and columnar optical depth (Kokhanovsky et al., 2005;Lewis and J., 1994;Schaaf et al., 2002).

25   Following Kokhanovsky et al. (2005), we calculated the Lambertian surface albedo at MODIS bands of 469, 555, 645, and 858 nm by weighting the contributions of white-sky and black-sky albedos.

The differences in spectral position and width of corresponding EPIC and MODIS channels may result in discrepancies. To compensate, we adjust MODIS reflectance values to equivalent EPIC-bands. The adjustment factors, in the forms of linear regression coefficients, were determined from analyzing USGS (the United States Geological Survey) hyperspectral data for

30   green vegetation. Figure 6a shows the selected reflectance spectra of 47 vegetation samples from the USGS Spectral Library Version 7 (Kokaly et al., 2017) and spectral locations of EPIC (blue) and MODIS (red-dotted) bands. Linear regression of reflectance values at each EPIC band and corresponding MODIS band is illustrated as scatterplots in Figure 6c-h. The regression slope and offset, as well as coefficient of determination (R^2), are listed in Figure 6b. As shown, the reflectance

between EPIC bands and their closest MODIS bands are highly correlated (R^2 from 0.96 to 1.0), and therefore, best-fitting equations in Figure 6b can be used to empirically derive EPIC surface reflectance from MODIS surface reflectance products.

The retrieval also requires auxiliary meteorological information to realistically characterize O_2 absorption properties. Surface pressure strongly affects the reflectance in O_2 absorption bands as observed from space, because it is a direct proxy

5   for the columnar loading of air (and thus oxygen) molecules. Here, we enlisted surface pressure information from the Modern-Era Retrospective analysis for Research and Applications Version 2 (MERRA-2) datasets (Gelaro et al., 2017). MERRA-2's 1-hourly surface pressure at 0.5° by 0.675° grids were interpolated to the location and scan time of each EPIC pixel. In addition, the atmospheric temperature-pressure profile also impacts the width and strength of O_2 absorption lines. However, such influence on the radiative transfer is negligible for EPIC's 1-to-2-nm-wide bands. In this study, our algorithm

10   employs a standard temperature-pressure profile representing the mid-latitude-summer atmosphere (McClatchey et al., 1972).

3.4 Mask clouds, sun glints, and bright land surface

After acquiring EPIC TOA reflectance and surface reflectance, the algorithm conducts a masking exercise to select clear-sky pixels suitable for aerosol retrieval. This includes the screenings of clouds, sun glint over water surfaces, and highly

15   reflective land surfaces. Over both the land and water, the cloud mask combines a set of brightness and homogeneity tests following Martins et al. (2002). The brightness tests screen out cloud pixels where EPIC TOA reflectance in two or three visible bands (443 and 680 nm over land; 443, 680, and 780 nm over water) exceed prescribed thresholds. The homogeneity test, on the other hand, identifies cloud pixels by evaluating the standard deviation of TOA reflectance at 443 and 551 nm within 3×3 neighboring pixels. Still, thin and small subpixel clouds can be missed in the relatively coarse resolution 8 km

20   EPIC pixels, leading to an overestimation of AOD and an underestimation of ALH. Therefore, contamination by small-scale clouds is one of the known issues of retrieval quality and coupling higher-resolution geostationary sensors' cloud mask information may help to overcome this issue. Besides, cloud mask thresholds used in this work might need to be adjusted if applied operationally.

In addition, EPIC pixels affected by sun glint and highly-reflective land surface are also removed from consideration by the

25   mask. We identify the over-water glint area as those pixels having a glint angle smaller than 30° (Levy et al., 2013). Highly reflective land-surface pixels are identified with MODIS land surface products. Any EPIC pixel having NDVI below 0.2 or having a 680 nm surface reflectance larger than 0.1 is flagged as being a bright surface and excluded from the retrievals.

3.5 Look-up tables

Following Xu et al. (2017), the revised algorithm retrieves smoke ALH and AOD from EPIC measurements via a set of

30   lookup tables (LUTs) constructed with UNL-VRTM model. The UNL-VRTM (https:// unl-vrtm.org) is a radiative transfer testbed developed specifically for atmospheric remote sensing (Wang et al., 2014). By integrating the VLIDORT vector radiative transfer model (Spurr, 2006) and particulate scattering codes (Spurr et al., 2012), UNL-VRTM can perform simulations for two or more sets of aerosol microphysical properties, typically with aerosols in one fine mode and one coarse

mode. It also incorporates the HITRAN spectroscopic gaseous absorption by up to 22 trace gases (Rothman et al., 2013), allowing for accurate hyperspectral simulations of remote sensing observations (Xu et al., 2018b).

The LUTs of the current retrieval consist of simulated EPIC TOA reflectance at selected spectral bands for a set of AOD and ALH values under various atmospheric and observation circumstances (e.g., sun-earth-sensor geometry, surface reflectance,

5 and surface pressure) as shown in Table 1. To build the LUTs, hyperspectral monochromatic radiances were simulated by UNL-VRTM and convolved with EPIC instrumental filter response functions at the selected 6 bands. Table 2 provides the spectral range, interval, and resolution (in terms of full-with at half maximum; FWHM) of the UNL-VRTM simulations.

The UNL-VRTM simulations assume a Gaussian-like aerosol profile characterized by a centroid altitude and a half-width parameter (Spurr and Christi, 2014;Xu et al., 2017). The centroid altitude is taken to represent ALH. A half-width of 1 km is

10 assumed by following Xu et al. (2017). This value was also used to derive AOD from UV observations by the Total Ozone Mapping Spectrometer (TOMS) and the Ozone Monitoring Instrument (OMI) (Torres et al., 1998). For this study, we implemented smoke optical properties calculated based on Lorenz-Mie scattering theory. Smoke refractive index was assumed to be $1.5 - 0.012i$, following Dubovik et al. (2002), and its spectral dependence was neglected. We assumed smoke particles followed a bi-lognormal size distribution, as adopted for the MODIS dark-target aerosol algorithm (Levy et al.,

15 2013;Remer et al., 2005). Specifically, fine-mode volume median radius and standard deviation were prescribed as $0.14 + 0.01\tau_{680}$ μm and 0.44, respectively. The coarse-mode counterparts are $0.14 + 0.01\tau_{680}$ μm and 0.80, respectively. The volume ratio between fine and coarse modes is $(0.01 + 0.3\tau_{680})/(0.01 + 0.09\tau_{680})$. Here, τ_{680} is total AOD at the wavelength of 680 nm.

3.6 Strategy of flexible spectral fittings

20 The retrieval procedure involves two steps over both the water and land surfaces and, at the same time, incorporates flexible spectral fittings that account for specifics of surface reflectivity. First, TOA reflectance in EPIC's "atmospheric window" channels are matched with LUTs to determine AOD, because at these channels the TOA reflectance is independent of ALH. Second, based on this estimated AOD, the DOAS ratios around the O₂ bands are fitted to estimate ALH. In each step, least-squared fitting is applied, and fitting residuals are reported.

25 In general, retrieving aerosol information from reflected solar radiation in vis-to-NIR wavelengths over land is more challenging than over ocean, because over land the satellite signal tends to be dominated by surface contributions over land. It is thus often the case that, for the same satellite instrument, separated over-land and over-ocean algorithms are developed with different strategies in characterizing surface reflectivity and band selection for fitting, e.g., MODIS aerosol algorithms (Remer et al., 2005). Similarly, our retrieval of smoke ALH from EPIC uses different band combinations over land versus

30 over ocean, adjusted by the surface type and spectral signature of smoke aerosol in the TOA reflectance.

In general, reflectance of water surfaces does not exceed 0.03 across the entire vis-to-NIR spectrum (Figure 4). Therefore, AOD can be determined by fitting TOA reflectance in all of the four "atmospheric window" channels at 443 nm, 551 nm, 680 nm, and 780 nm. In contrast, the band of 780 nm is excluded for the spectral fitting over vegetated land surface because

of the high chlorophyll reflectance. Similarly, in the fitting of DOAS ratios, weights to ratios in the O_2 A and B bands are given differently for different surfaces, adjusted by the sensitivity of the DOAS ratio to ALH (e.g., Figure 3). The weighting coefficients are 0.4 for $R688/R680$ and 0.6 for $R764/R780$ over water surface, whereas these values are 0.9 and 0.1 over vegetated surface.

4. Retrieval Demonstration

We apply our algorithm to six EPIC scenes over the Hudson Bay – Great Lakes area obtained during 25 – 26 August 2017, with three consecutive scenes considered on each day. We chose these cases primarily because smoke plumes prevailed over both water and vegetated surface, and there were available aerosol vertical profile measurements from CALIOP that could be used to validate the ALH retrievals. As shown in EPIC RGB images (Figures 7a and 8a), smoke aerosols appeared as diffuse plumes emitted from wildfires in western Canada and, crossing over the western and southern portions of Hudson Bay (Peterson et al., 2018). The retrieved smoke ALH are shown in Figure 7b and 8b; and retrieved 680-nm AOD in Figure 7c and 8c. It is noted that data gaps in the AOD maps represent screened-out bright pixels due to either cloud or land surface; and ALH retrievals were only available when AOD was larger than 0.2.

Obvious spatial variations are noted in retrieved smoke ALH and AOD. On August 25, smoke plumes had AOD values ranging from 0.1 to 0.45, with higher loading found at downwind regions in the south (Figure 7c). An ALH of 4 – 5 km was found over Hudson Bay, whereas the smoke altitudes decreased to 2 – 4 km over land off the bay's western and southern shores (Figure 7b). Southward, the ALH increased rapidly to 4 – 6 km towards the Great Lakes. By August 26, the smoke plumes had traveled towards southeast (Figure 8c). The smoke altitudes remained at 3 – 5 km over the eastern part of Hudson Bay, and 2 – 4 km over the bay's south side (Figure 8b). Altitudes of smoke plumes over the coast of northeastern U.S. were higher than 5 km. Aside from spatial variations, the retrievals also revealed diurnal changes of ALH and evolution of the smoke plumes. For instance, the ALH of smoke plumes over the Hudson Bay and the north side of the Great Lakes rose by about half km within two hours from local morning to afternoon on August 25 (Figure 7b).

5. Retrieval validations

For the validation of the EPIC-retrieved ALH, we used CALIOP Level 2 version 4.10 aerosol extinction profiles at 5 km spatial resolution, retrieved from CALIOP observation of attenuated backscatter at 532 nm (Young and Vaughan, 2009). To facilitate quantitative comparison of aerosol altitude, we used a mean extinction height calculated from the CALIOP extinction profile, following Koffi et al. (2012):

$$\text{ALH}_{\text{CALIOP}} = \frac{\sum_{i=1}^{n} \beta_{\text{ext},i}\, Z_i}{\sum_{i=1}^{n} \beta_{\text{ext},i}} \quad (2)$$

Here, $\beta_{\text{ext},i}$ is the aerosol extinction coefficient (km^{-1}) in 532 nm at level i and Z_i is the altitude (km) of level i. Thus, $\text{ALH}_{\text{CALIOP}}$ represents an effective ALH weighted by aerosol extinction signal at each level and is consistent with ALH defined in our EPIC algorithm.

In the CALIOP Level 2 products, aerosol extinction is only retrieved with the layers where aerosols are detected, as permitted by the instrument's signal-to-noise ratio (SNR). Atmospheric layers with no aerosols detected are classified as "clear air" and assigned an aerosol extinction coefficient of 0 km⁻¹. The detection limits are defined in terms of backscattering ratio that depends on an aerosol lidar ratio (Vaughan et al., 2009). As such, aerosol layers that span a large

5 altitude range frequently remain undetected (Toth et al., 2018), particularly for absorbing aerosols in the day time. As indicated by Winker et al. (2013), aerosol extinction threshold in daytime CALIOP scan is $0.01 - 0.03$ km⁻¹ for 80-km averaging resolution and reaches up to 0.07 km⁻¹ for 5-km averaging resolution. In reality, aerosols are ubiquitous throughout the troposphere, though the concentration can be very low in the free troposphere. However, excluding the "clear-air" layers would lead to a biased estimate of ALH_{CALIOP}, particularly for cases of predominately "clear-air" layers

10 present below an elevated aerosol layer. To compensate for this bias, we use a exponentially-decayed background aerosol extinction profile for substitute of aerosol extinction coefficients of these undetected aerosol layers within troposphere. The background profile has a columnar AOD of about 0.07 at 532 nm, according to Tomasi and Petkov (2014), who use various lidar measurements to characterize the summertime atmosphere of the Arctic. Though aerosol extinction within the undetected aerosol layers by no means follows the background extinction profile identically, adding such a background

15 aerosol extinction profile can, to first order, correct the potential bias of ALH_{CALIOP}.

Figure 9 presents the evaluation of our ALH retrieval against CALIOP observations, showing that the ALH retrieval captures the overall spatial variability of ALH as seen by CALIOP. Quantitatively, 67% and 59% of the retrievals are within 0.5 km difference from the counterparts of ALH_{CALIOP} on August 25 and 26, respectively. Considering all EPIC- CALIOP ALH pairs, 65% of ALH retrieval are within uncertainty envelope of 0.5 km (Figure 10a); and EPIC ALH has a mean bias of –

20 0.13 km and a root-mean-squared-error (rmse) of 0.58 km, capturing 52% variation of the ALH_{CALIOP}.

The EPIC 680 nm AOD retrievals during the two days were compared against observations of 675 nm AOD at nine AERONET sites (Table 3). The collocation method follows (Ichoku et al., 2002), but was modified to associate a subset of satellite retrievals within a 3×3 AOD subset centered at each site to a subset of 1-hour AERONET observations around EPIC scan time. Collocated AERONET AOD values at each site are shown as circles in Figure 7c and 8c. Comparison of

25 EPIC AOD and AERONET are shown in Figure 10b. The collocated AOD pairs, though with limited data samplings, have over 77% falling in an error envelope of $\pm (0.05 + 10\%)$ with a coefficient of determination (R^2) of 0.54. EPIC AOD shows a positive bias of 0.03 and a rmse of 0.05, which was dominated for four subsets of EPIC AODs and was likely caused by cloud contamination.

6. Implication to the retrieval of UV absorbing aerosol properties

30 One important implication of this study is that the retrieved ALH can provide complementary height information for determining absorbing aerosol properties from EPIC's UV bands. EPIC also measures backscattered UV radiances at 340 nm and 388 nm, which was designed to detect and retrieve optical properties of UV-absorbing aerosols like mineral dust and smoke by using UV aerosol index (UVAI) (Marshak et al., 2018). UVAI quantifies the difference in spectral dependence between measured and calculated near UV radiances assuming a purely molecular atmosphere (Torres et al., 1998).

Physically, inferring aerosol properties from those UV bands requires the characterization of aerosol height, because UV radiance is sensitive to aerosol vertical distribution. For example, Jeong and Hsu (2008) retrieve aerosol single scattering albedo (SSA) from OMI radiance via synergic use of AOD from MODIS and ALH from CALIOP. Currently, EPIC's UV aerosol algorithm utilizes climatological aerosol height data set derived from CALIOP observations (Torres et al., 2013).

5   However, these static climatological data may fail to capture the dynamic variation of aerosol height, and thus induce uncertainties in the UV-retrieved aerosol properties. With the aerosol height and loading available from the EPIC's O_2 A and B bands, these closures are now possible with measurements from a single instrument. Such synergy can be also applied to the TROPOspheric Monitoring Instrument (TROPOMI) and the Plankton, Aerosol, Cloud, ocean Ecosystem (PACE) satellite, both perform hyperspectral measurements from UV to NIR and cover both the O_2 A and B bands (Veefkind et al.,

10   2012;Omar et al., 2018).

Here, we compare our retrieved ALHs with EPIC UVAI to illustrate the importance, as well the potential benefit, of the ALH retrievals to EPIC's UV aerosol products. The EPIC UVAI data are publicly available at https://eosweb.larc.nasa.gov/project/dscovr/ (last accessed Nov 26, 2018). Figure 11 shows the UVAI of the same EPIC scenes on August 25. These smoke plumes are highlighted by large values of UVAI, which are in contrast to clouds which

15   typically exhibit a UVAI close to zero (Torres et al., 1998). Because UVAI is a function of ALH, AOD, and SSA, its correlation with ALH varies with AOD. As shown in Figure 12, the sensitivity of UVAI to ALH, as well as correlation between them, increases as AOD increases. In particular, high AOD values (e.g., over 0.4) may results in a value UVAI from less than 1 to about 4, depending on the ALH (Figure 12, bottom-right panel). Therefore, the use of ALH derived from the EPIC's O_2 bands is expected to improve EPIC UV aerosol retrievals.

20   **7. Summary and discussions**

Based on our previous efforts in retrieving over-water dust ALH from the EPIC (Xu et al., 2017), we extend the retrieval algorithm to biomass burning smoke aerosols over both the water and vegetated land surfaces. The new algorithm uses earth-reflected radiances in EPIC's visible and NIR bands and incorporates flexible spectral fittings that account for specifics of vegetation and water surface reflectivity. The fitting procedure first determines AOD using four EPIC atmospheric window

25   bands (443 nm, 551 nm, 680 nm, and 780 nm), then uses the DOAS ratios formulated in the O_2 A and B bands (688 nm and 764 nm) to derive the ALH that represents an optical centroid altitude. ALH retrieval over vegetated surface primarily takes advantage of the measurements in the O_2 B band, where surface reflectance is sufficiently low to yield aerosol height information. And, surface reflectance values are determined with MODIS surface products over land and GOME-2 LER products over ocean.

30   We applied the algorithm to six EPIC images, with 3 images on each day, having biomass burning plumes over the United States and Canada acquired on 25 – 26 August 2017. We found the algorithm captures AOD and ALH multiple times daily over both the water and vegetated land surfaces. The retrieved ALHs were validated against CALIOP extinction weighted aerosol height (ALH$_{CALIOP}$), showing EPIC retrieved ALH has a rmse of 0.58 km and captures 52% variation of the ALH$_{CALIOP}$, and 65% of EPIC and CALIOP ALH pairs are within an uncertainty envelope of 0.5 km. EPIC retrieved AODs

are validated against AERONET AOD observed at nine sites, indicating a mrse of 0.05 and over 77% of EPIC AOD retrievals fall within the error envelope of ± (0.05 + 10%). In addition, by comparing the retrieved ALH and EPIC UVAI, we show that the aerosol height information retrieved by the present algorithm can potentially benefit the retrieval of aerosol properties from the EPIC's UV bands.

5 The over 3 years of data recorded thus far by EPIC (July 2015 – present) offers an opportunity to characterize aerosol height from diurnal to seasonal scales. Such datasets with well-characterized uncertainties are valuable for evaluating aerosol vertical distribution simulated by climate models. A follow-on study, based on the current work and Xu et al. (2017), will examine the long-term global retrieval of ALH for dust and smoke aerosols. Challenges for such a global retrieval include the heterogeneity of aerosol species, whereas our efforts have been mainly focused on single-species dust or smoke aerosol

10 assumptions. In fact, mixtures of aerosol are more commonly found in nature. Furthermore, the currently available EPIC UVAI products can help identify elevated absorbing aerosols (mainly, dust and smoke), which can then be used to determine the retrieval targets on any EPIC image.

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Tables

Table 1. Adopted parameters for generating LUTs.

Parameter*	Prescribed values for LUTs
AOD at 680 nm	0.0, 0.1, 0.2, 0.4, 0.7, 1.0, 1.5, 2.0, and 3.0
ALH above surface (km)	0 to 15 km at 1 km interval
Surface reflectance	0, 0.05, 0.1, 0.2, 0.3, 0.4, and 0.6
θ_0 and θ (°)	0° to 72° at interval of 6°, and $\lvert\theta_0 - \theta\rvert < 15°$
$\Delta\varphi$ (°)	0° to 180° at interval of 12°,
Surface pressure (hPa)	700, 800, 900, and 1050

*θ_0 indicates the solar zenith angle, θ the satellite viewing zenith angle, and $\Delta\varphi$ the relative azimuth angle

5

Table 2. Spectral settings of UNL-VRTM in constructing the LUTs

EPIC channel (nm)	Spectral range (nm)	Spectral interval (nm)	FWHM (nm)
443	440 – 445	0.1	0.2
551	549 – 555	0.1	0.2
680	675 – 685	0.1	0.2
688	685 – 690	0.01	0.02
764	760 – 766	0.01	0.02
780	776 – 782	0.1	0.2

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Table 3. AERONET sites selected for AOD validation

Site name	Latitude (°)	Longitude (°)	N_{AOD}*
Billerica	42.53	− 71.27	3
Churchill	58.74	− 93.82	3
Egbert	44.23	− 78.78	2
Lake_Erie	41.83	− 83.19	2
LISCO	40.76	− 73.34	4
NEON_UNDE	46.23	− 89.54	2
Pickle_Lake	51.45	− 90.22	1
Thompson_Farm	43.11	− 70.95	3
Toronto	43.79	− 79.47	2

* N_{AOD} is the number of collocated AERONET AOD values

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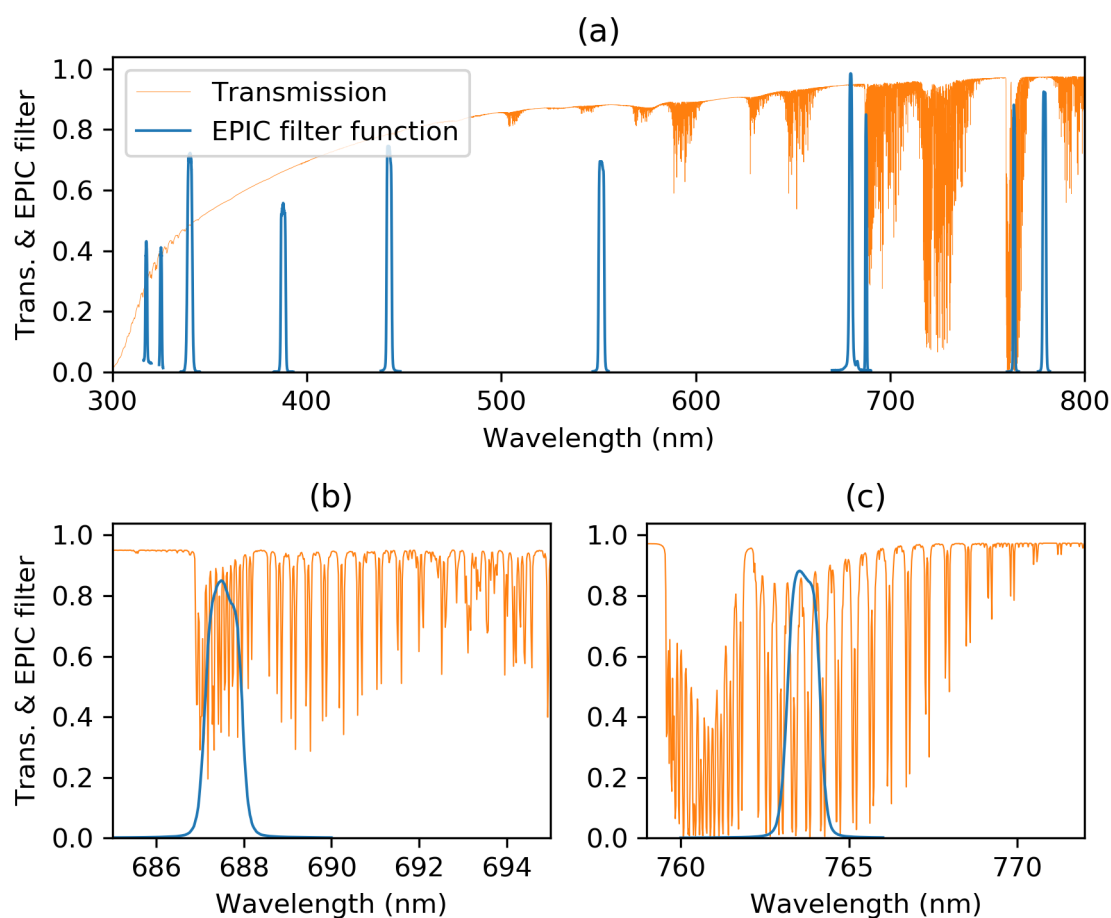
Figures

5 **Figure 1.** Filter response functions the EPIC instrument (blue) and atmospheric spectral transmission (orange). Panel (a) includes all the ten EPIC bands, whereas panels (b) and (c) show zoom-ins for 688-nm band in the O_2 B-band and 764-nm channel in the O_2 A-band, respectively. Here the atmospheric transmission is simulated by the UNL-VRTM model with a spectral step and a spectral full width at half maximum of 0.02 nm.
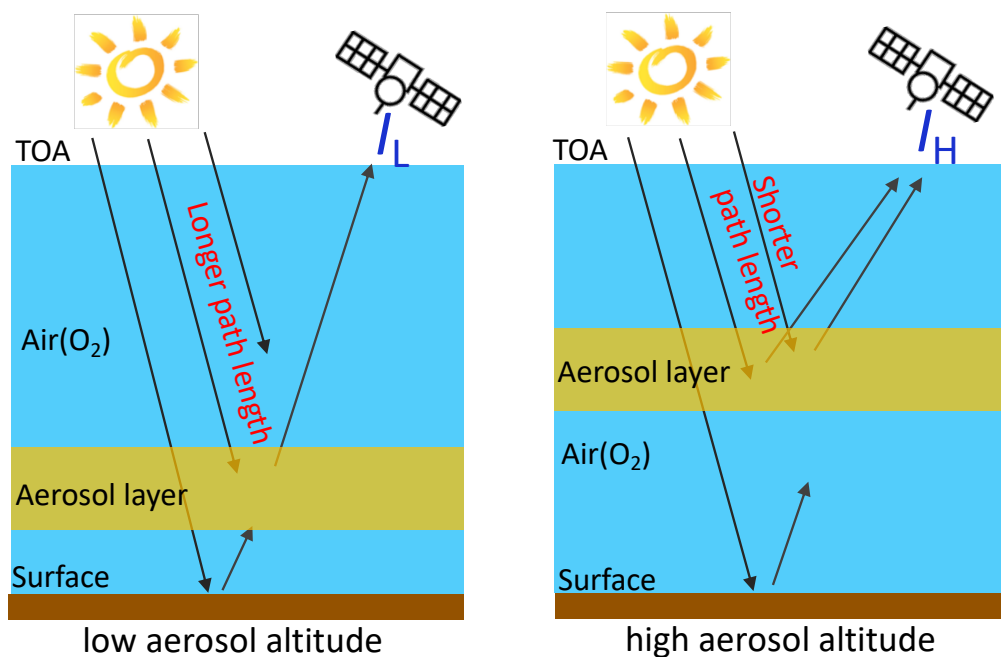
Figure 2. Schematic diagram of the physical principal for remote sensing of aerosol layer height in the O_2 absorption bands. Shown is the same aerosol layer located at two different altitudes in the atmosphere. Due to the scattering of aerosol particles, photons scattered by a higher aerosol layer (right panel) would travel a shorter path way to reach the satellite sensor than in the lower-altitude aerosol (left panel), resulting in a less chance of absorption by O_2 and thus a higher radiance detected by the satellite (i.e., $I_H > I_L$).
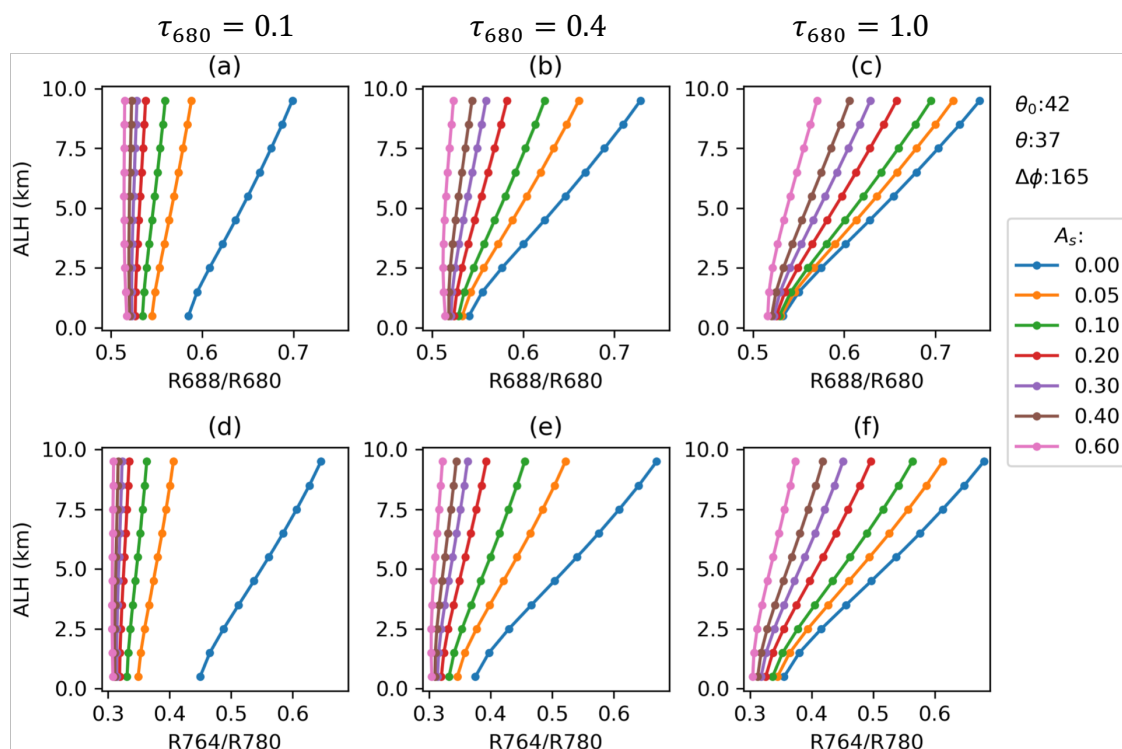
Figure 3. Sensitivity of DOAS ratios of TOA reflectance around the O_2 A and B bands to smoke ALH as simulated by UNL-VRTM for different AOD and surface reflectance values. Simulations were performed for a typical biomass-burning aerosol model as observed by EPIC at the geometry of $[\theta_0, \theta, \Delta\phi] = [42°, 37°, 165°]$, where θ_0 and θ are solar and viewing zenith angles, and $\Delta\phi$ the relative azimuth angle.
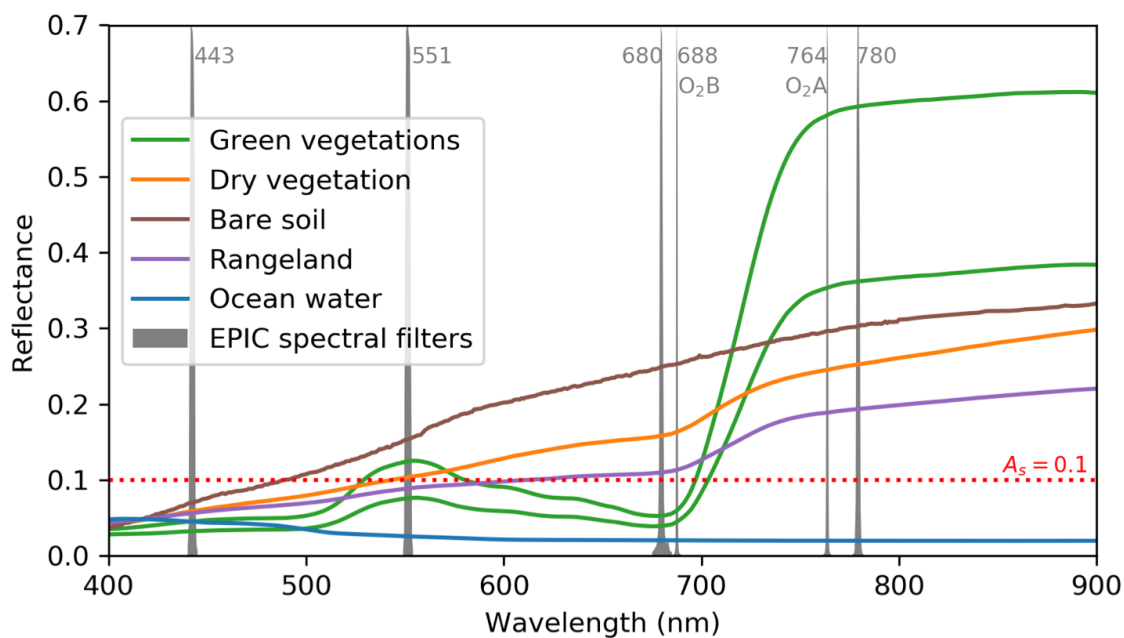
Figure 4. Surface reflectance spectra (from the ASTER spectral library; Baldridge et al., 2009) for various surface types in the visible-to-NIR range, with selected EPIC spectral bands within this range shown in gray.
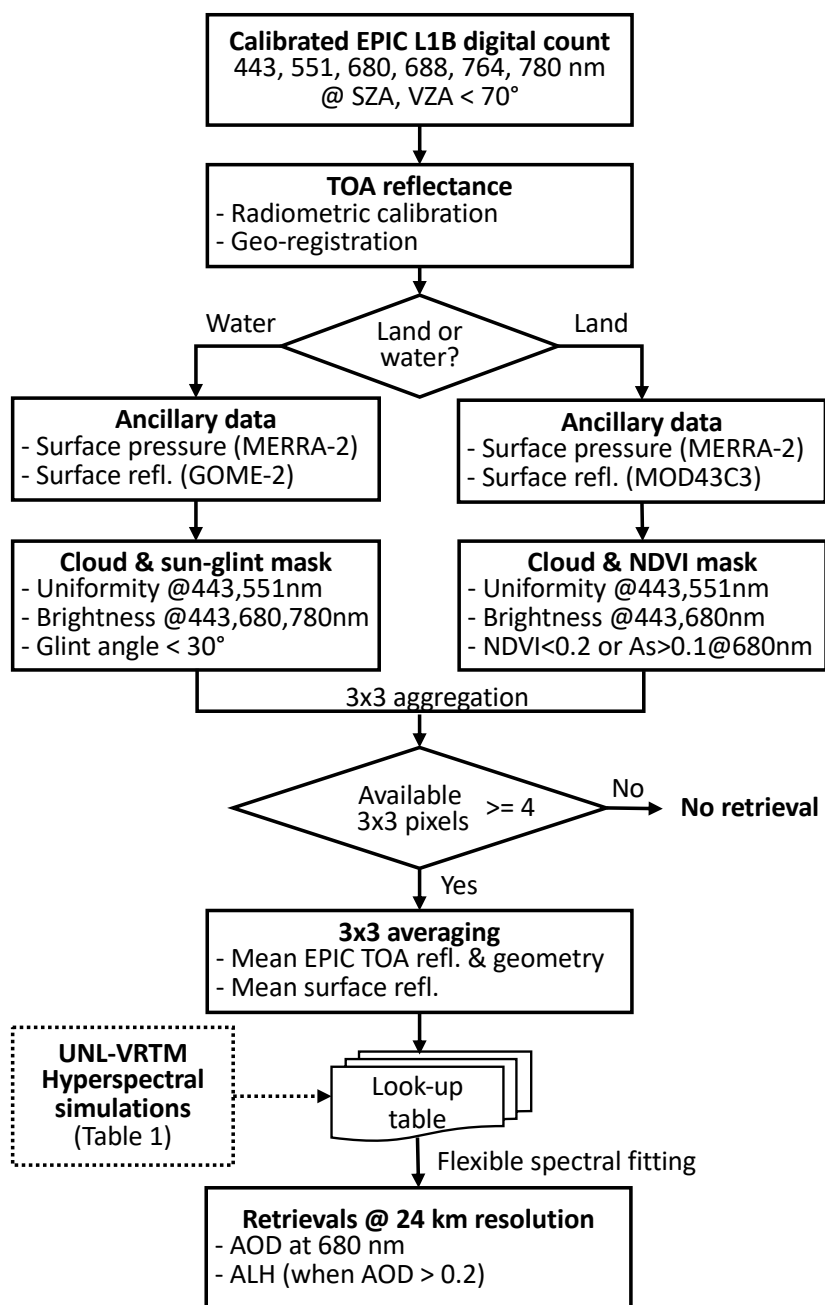
Calibrated EPIC L1B digital count
443, 551, 680, 688, 764, 780 nm
@ SZA, VZA < 70°

TOA reflectance
- Radiometric calibration
- Geo-registration

Water   Land or   Land
           water?

Ancillary data
- Surface pressure (MERRA-2)
- Surface refl. (GOME-2)

Ancillary data
- Surface pressure (MERRA-2)
- Surface refl. (MOD43C3)

Cloud & sun-glint mask
- Uniformity @443,551nm
- Brightness @443,680,780nm
- Glint angle < 30°

Cloud & NDVI mask
- Uniformity @443,551nm
- Brightness @443,680nm
- NDVI<0.2 or As>0.1@680nm

3x3 aggregation

Available
3x3 pixels   >= 4   No   **No retrieval**

Yes

3x3 averaging
- Mean EPIC TOA refl. & geometry
- Mean surface refl.

**UNL-VRTM
Hyperspectral
simulations**
(Table 1)

Look-up
table

Flexible spectral fitting

Retrievals @ 24 km resolution
- AOD at 680 nm
- ALH (when AOD > 0.2)

Figure 5. Flowchart of the AOD/ALH retrieval algorithm.

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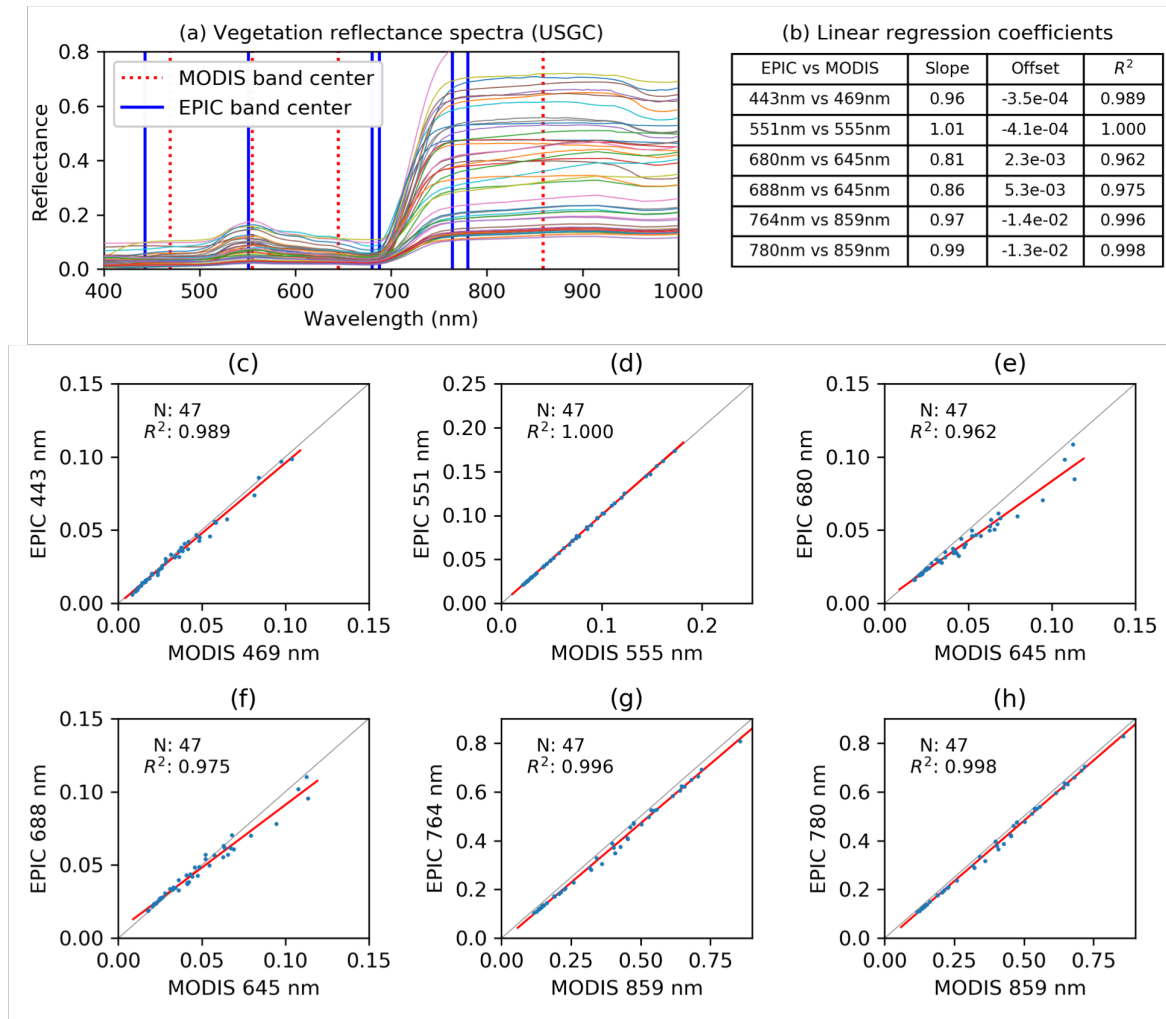
Figure 6. Determination of surface reflectance from MODIS surface albedo products. (a) USGS reflectance spectra for different vegetation samples, and (b) the statistics for regression (i.e., slope, offset, and coefficient of determination, R^2) of reflectance between different EPIC bands, marked as red dot line in (a), and their respective closest MODIS bands, marked as blue lines in (a), according to the spectral library. (c-f) Scatterplots of reflectance at each EPIC band versus reflectance at corresponding MODIS bands. Linear regression lines are shown in red.
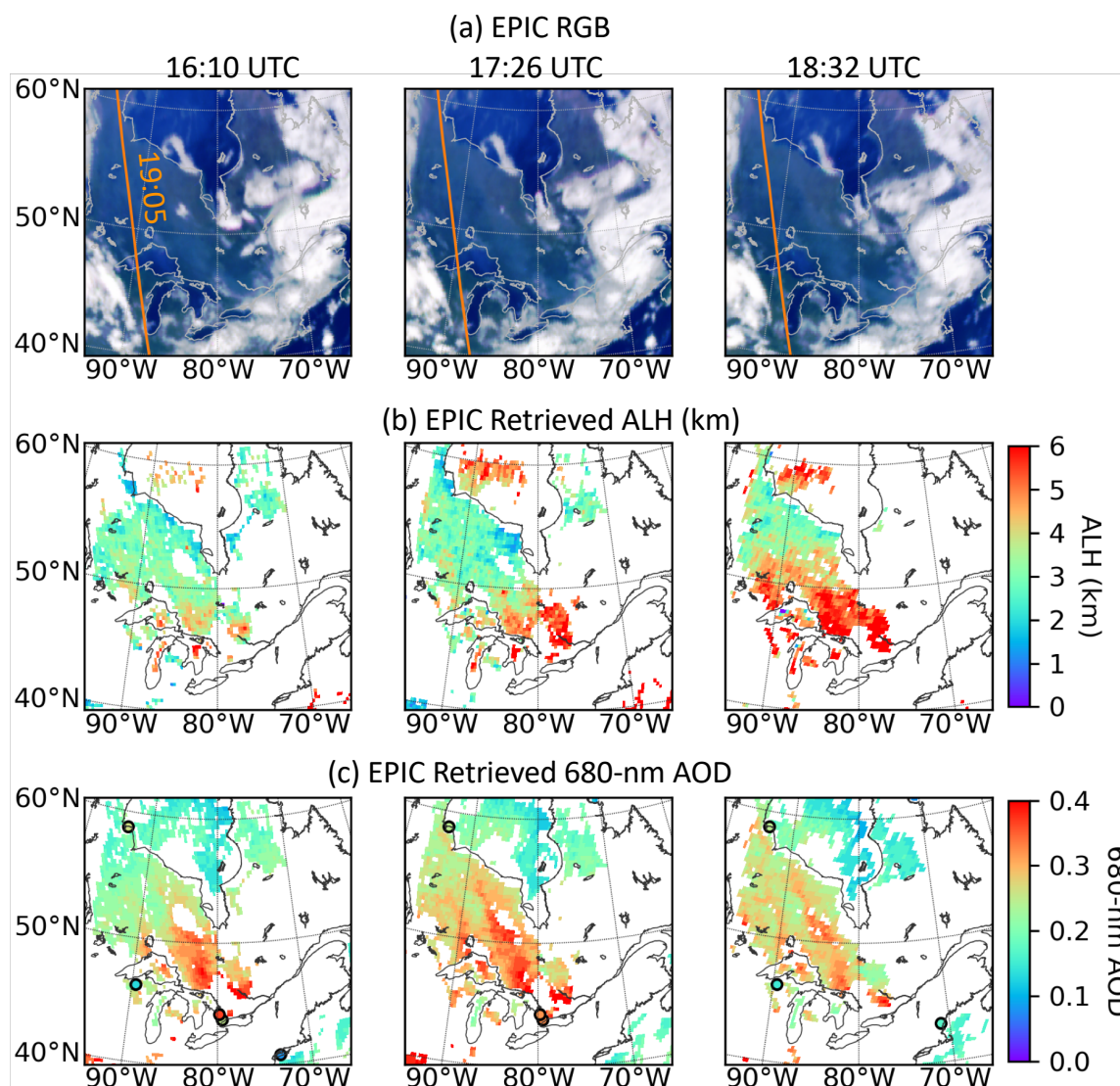
Figure 7. Demonstration of ALH and AOD retrievals for three EPIC scenes acquired on 25 August 2017 around UTC time of 16:10, 17:26, and 18:32. (a) RGB composites of EPIC 443 nm, 551 nm, and 680 nm data. The gold line indicates CALIOP sub-orbital track with an overpass time 19:05 UTC. (b) Retrieved smoke ALH when 680-nm AOD is larger than 0.2. (c) Retrieved 680 nm AOD. Small circles on AOD maps represent AOD values observed at corresponding AERONET sites within two hours of EPIC scan time.
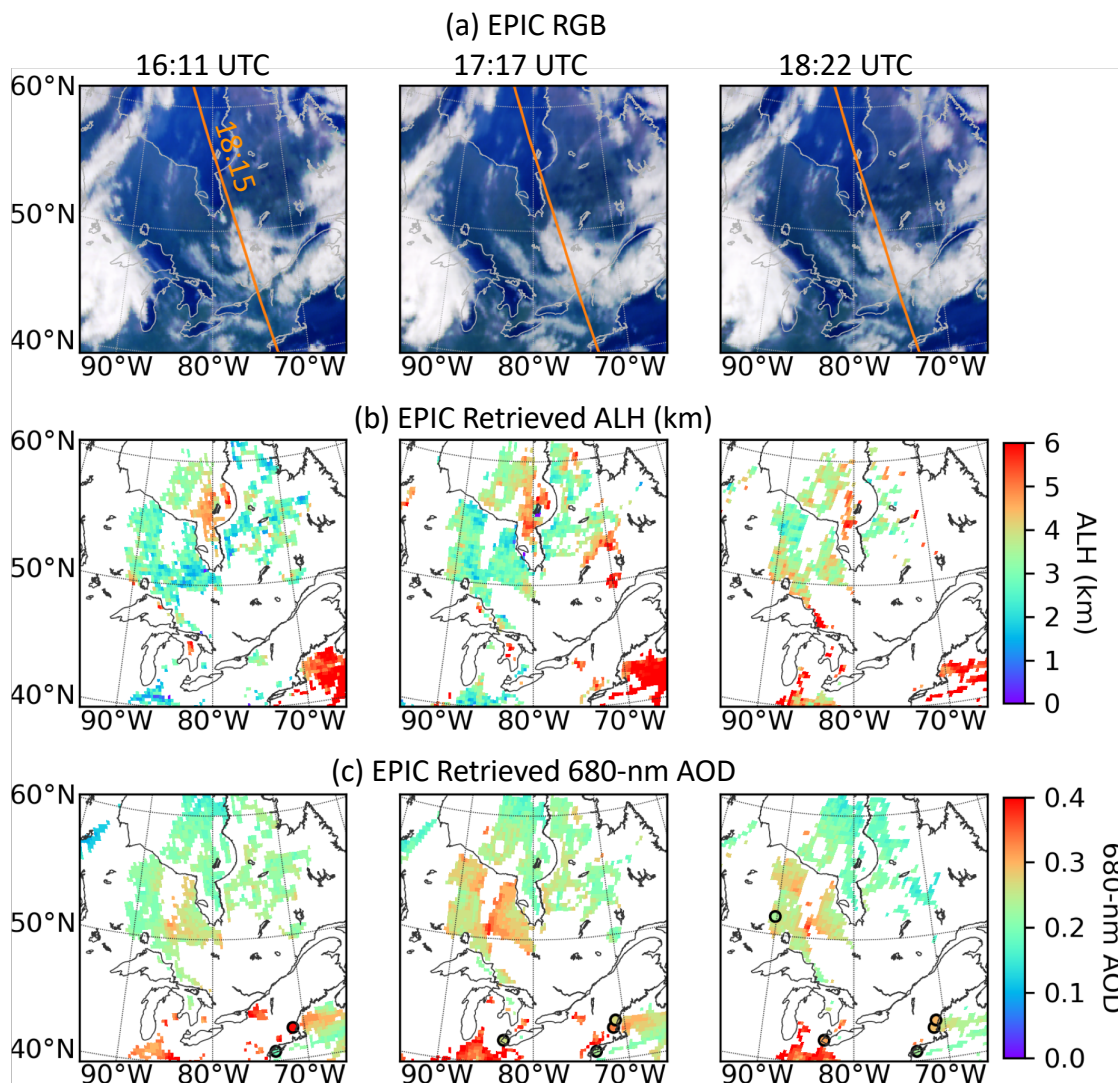
Figure 8. Same as Figure 7 but for three EPIC scenes captured on 26 August 2017 at UTC time of 16:11, 17:17, and 18:22. CALIOP overpass time was at 18:15.
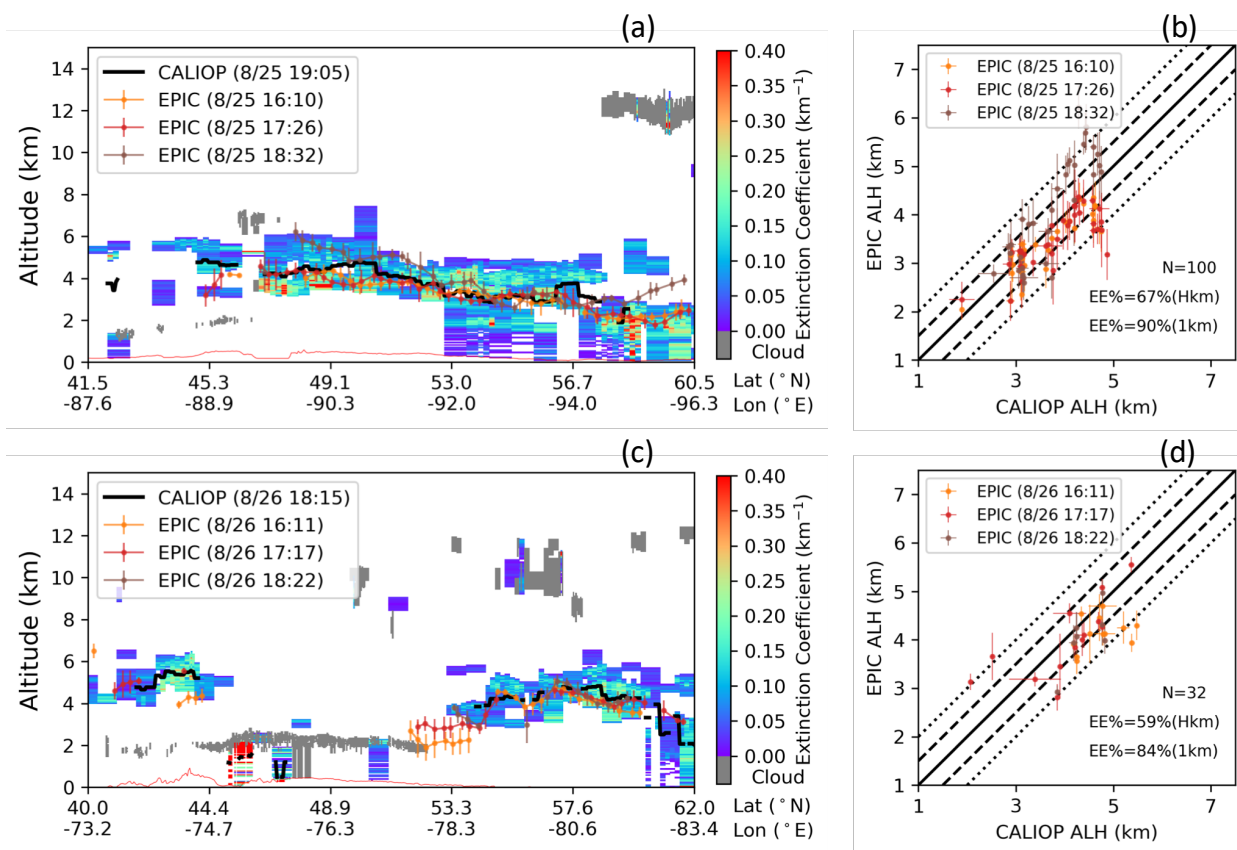
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Figure 9. Comparison of ALH retrieved from EPIC and the ALH derived from CALIOP level-2 aerosol extinction profile in both 'curtain' view (left column) and 'scatterplot' view (right column) for two-day overpasses. CALIOP orbital tracks are marked on EPIC RGB images in Figure 7–8. Different EPIC scan times are marked with different line/symbol colors in the comparison. Error bar of EPIC ALH represents standard deviation for an array of 3x3 24-km retrieval pixels, while the error bar of CALIOP ALH represents standard deviation of over 5 adjacent CALIOP 5-km footprints.
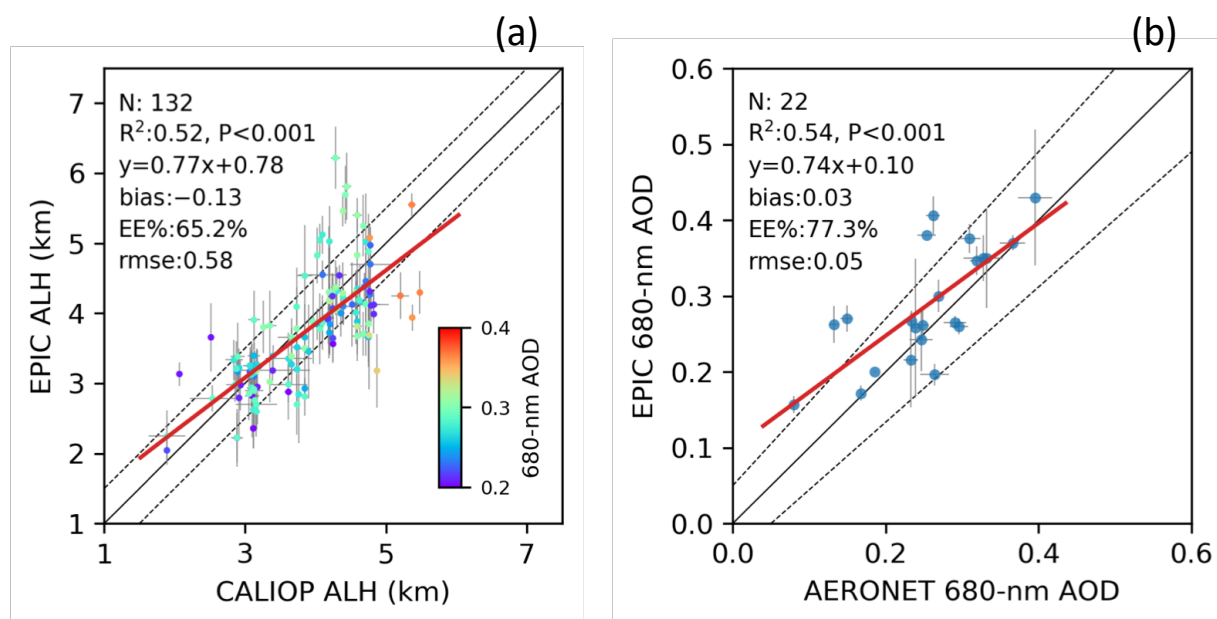
Figure 10. Comparison of EPIC ALH and AOD with the counterparts from CALIOP and AERONET measurements. (a) Scatterplot of EPIC ALH versus CALIOP ALH by including all EPIC-CALIOP pairs shown in Figure 9. Color of each scatter represents EPIC 680-nm AOD value of the same EPIC pixels. (b) Scatterplot of EPIC 680-nm AOD versus AERONET 675-nm AOD, collocated at 9 AERONET sites listed in Table 3. Dotted lines in both the scatterplots represent error envelops, i.e., $\pm$ 0.5 km for ALH and $\pm$ (0.05 + 10%) for AOD. Also annotated are one-by-one line (solid black line), linear regression fitting (red line), number of scatters (N), coefficient of determination (R^2), significance level (P), the linear regression equation, bias, percentage of scatters within error envelop (EE%), and root-mean-squared-error (rmse).
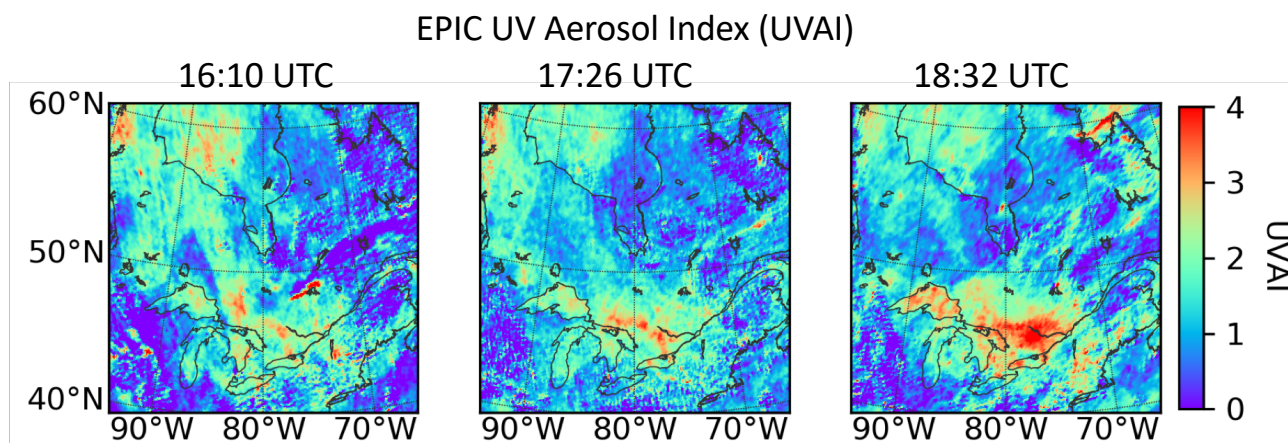
Figure 11. EPIC UV aerosol index (UVAI) for the three scenes on 25 August 2017 shown in Figure 7. Here the UVAI were
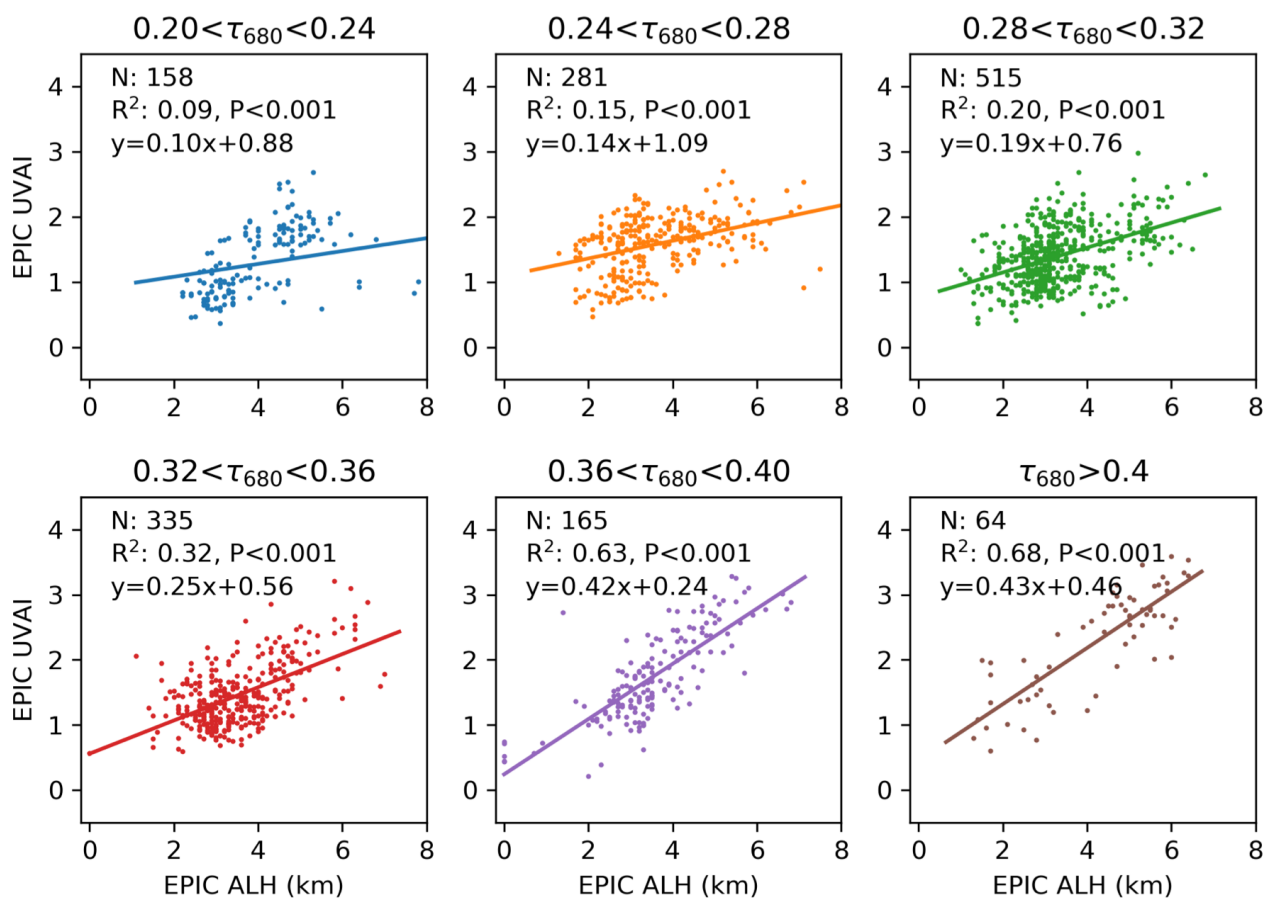obtained from EPIC Level-2 UV aerosol products.

Figure 12. Scatterplots of EPIC UVAI (Figure 11) versus current retrievals of ALH (Figure 7) on 25 August 2017 (17:26 UTC) under different AOD values as indicated in the title of each panel. Also annotated are linear regression fitting, number of scatters (N), coefficient of determination (R^2), and significance level (P).