

Retrievals of smoke particle properties using AirMSPI measurements acquired during FIREX-AQ field campaign

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HIGHLIGHTS

- Optimization-based retrieval of smoke properties from multi-angle polarimetry.
- Neural network-accelerated radiative transfer enables fast smoke retrieval.
- Multi-angle smoke retrievals affected by plume inhomogeneity and temporal change.
- Optimal view angles are suggested for AirMSPI retrievals of FIREX-AQ smoke plumes.

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ABSTRACT

- An optimization-based approach is developed to retrieve smoke particle properties from the observations acquired by the Airborne Multiangle SpectroPolarimetric Imager (AirMSPI) during the Fire Influence on Regional to Global Environments Experiment-Air Quality (FIREX-AQ) field campaign. This framework employs a three-step optimization strategy to mitigate the discontinuities between independently retrieved image patches. Moreover, it integrates a deep-neural-network-accelerated radiative transfer model to enhance retrieval efficiency. The retrieved aerosol products are compared with the AERONET reference data and the retrievals from the enhanced MODIS Airborne Simulator (eMAS). Under clear-sky conditions, retrieved aerosol optical depth (AOD) agrees with AERONET data within approximately ± 0.05 . For the smoke plumes with moderate to high AOD, the spatial patterns retrieved from AirMSPI are consistent with those from eMAS retrieval. The best agreement is achieved by excluding the four most oblique viewing angles (i.e., $\pm 65^\circ$ and $\pm 57^\circ$). Sensitivity tests indicate that using three to five AirMSPI angles within $\pm 45.8^\circ$ of nadir balances the mitigation of plane-parallel atmosphere modeling error while preserving the information richness of multi-angle observations of a three-dimensional plume. Moreover, single-view-angle retrievals, even when initialized with multi-angle retrieval results, still exhibit discrepancies relative to multi-angle retrieval. This is likely due to the coupled effects of the temporal evolution of smoke properties and the spatial inhomogeneity of smoke particles within the plume. The latter causes the multi-angle views to capture different portions of the plume and challenges the plane-parallel atmosphere model used in the retrieval.

1. Introduction

Polarimetry and multi-angle observations have greatly improved our ability to retrieve aerosol properties: offering higher accuracy and reduced ambiguities compared to traditional single-view, unpolarized measurements. By combining angular and polarization sensitivities,

multi-angle polarimetry provides strong constraints on key particle microphysics, such as size distribution, shape, and refractive index. As a pioneering satellite-borne multi-angle polarimeter, the Polarization and Directionality of the Earth's Reflectances (POLDER) instrument measures both radiometric and polarimetric signals along 16 angular directions in a set of visible to near-infrared bands, indicating the success

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of constraining aerosol absorption and microphysical properties simultaneously (Deschamps et al., 1994; Deuzé et al., 2001; Mishchenko and Travis, 1997). The POLDER is succeeded by the Multi-Viewing, Multi-Channel, Multi-Polarization Imager (3MI) on MetOp-SG (Fougnie et al., 2018) to cover a broader spectral range. Over the past two decades, some airborne multi-angle polarimeters (MAPs) such as the Research Scanning Polarimeter (RSP, Cairns et al., 1999), the Airborne Multiangle SpectroPolarimetric Imager (AirMSPI, Diner et al., 2013), AirHARP (Puthukkudy et al., 2020), and SPEX airborne (Smit et al., 2019), have also been developed. They capture high-resolution images in spatial, spectral, or angular domains, serving as highly valuable prototypes for satellite-borne sensors such as the Multi-Angle Imager for Aerosols (MAIA, Diner et al., 2018), HARP2 (McBride et al., 2024) and SPEXone (Hasekamp et al., 2019). The HARP2 and SPEXone polarimeters have been deployed by the PACE (Plankton, Aerosol, Cloud, ocean Ecosystem) mission (Werdell et al., 2019) which have been successfully launched recently, expanding our regional or global aerosol monitoring capabilities.

To retrieve aerosol properties from polarimetric observations, a variety of aerosol inversion algorithms have been developed, as summarized by (Dubovik et al., 2019; Kokhanovsky et al., 2007). As one of the prevailing approaches, the optimization-based retrieval that allows both observational and a priori physical constraints to be imposed on retrieval (Dubovik and King, 2000) has been successfully developed and applied to retrieve MAP data, or combined MAP and lidar measurements (Lopatin et al., 2021; Xu et al., 2021). In addition to real-data processing, optimization-based inversion approaches have been used to determine the optimal number and configuration of viewing angles and spectral bands needed to maximize the scientific return in retrieving aerosol geophysical variables, subject to a cost cap for a polarimetric sensor. It has been found that, while increasing the number and angular diversity of views generally improves sensitivity to aerosol microphysical properties, such as particle size distribution and refractive index (Mishchenko and Travis, 1997; Xu et al., 2016), the benefits tend to “saturate” beyond certain thresholds. For example, retrieval tests using simulated data and real airborne MAP measurements acquired from multiple field campaigns indicate a substantial gain of aerosol amount and single scattering albedo retrieved accuracy to be obtained from using two to five viewing angles, whereas a smaller gain is obtained when more than five angles (Wu et al., 2015; Xu et al., 2017). These studies, however, have focused on aerosol retrieval under clear-sky conditions, assuming plane-parallel atmospheric layers. Each layer is assumed to extend horizontally to infinity, with homogeneous concentration and bulk properties of aerosol particles. However, this assumption does not apply to aerosol emissions from wildfire smoke due to the spatial inhomogeneity of aerosol distribution and their properties. Several field campaigns have been conducted, deploying multiple types of airborne instruments to better investigate aerosol properties from smoke plumes and their impact on the regional climate. For example, the Fire Influence on Regional to Global Environments Experiment-Air Quality (FIREX-AQ) campaign focused on wildfire events in the western United States (Warneke et al., 2023), with the objectives to quantify fire emissions and to understand their evolution and impact on atmospheric composition and air quality. FIREX-AQ provides a valuable opportunity to evaluate the performance of MAP retrievals in smoky conditions and to assess how angular sampling geometry affects aerosol characterization in such complex environments.

Most existing multi-angle polarimetric aerosol inversion algorithms are based on the independent pixel approximation and implicitly or explicitly assume horizontal homogeneity of aerosol and surface properties within each retrieval column, consistent with a plane-parallel atmospheric representation. This assumption is generally reasonable under clear-sky or regionally uniform aerosol conditions, and has been widely adopted in MAP retrieval studies. However, wildfire smoke plumes represent a fundamentally different observational regime. They are characterized by strong three-dimensional structure, sharp

horizontal gradients, and rapid spatio-temporal evolution, all of which violate the horizontal homogeneity assumption underlying traditional inversion frameworks. As a result, different viewing angles of a multi-angle polarimeter may sample physically distinct portions of the plume, leading to systematic modeling errors when all views are interpreted within a single atmospheric column of plane-parallel structure. These challenges motivate the present study, which uses AirMSPI observations acquired during the FIREX-AQ campaign as a testbed to systematically examine and mitigate the limitations of conventional MAP aerosol retrievals in complex wildfire plume environments. In this work, we aim to develop an efficient yet improved AirMSPI algorithm to characterize aerosol particles generated from plumes. The instrument was installed in the nose section of an ER-2 aircraft. During the FIREX-AQ campaign, the AirMSPI provided multi-angular spectra-polarimetric images of smoke plumes with high spatial resolution. Through case studies, we will demonstrate the influence of 3-D geometry of plumes on the accuracy of aerosol retrieval which assumes a plane-parallel atmosphere and seek an optimal set of viewing angles to mitigate this impact. The paper is organized as follows: the general structure of the inversion algorithm is described in Section 2, followed by descriptions of the datasets used in this study in Section 3. Section 4 describes validation of the AirMSPI retrievals against the reference data acquired by the ground-based Aerosol Robotic Network (AERONET) and the aerosol products of enhanced-MODIS Airborne Simulator (eMAS, Ellis et al., 2011). Furthermore, the impacts of viewing angle sampling on aerosol optical depth (AOD) retrieval are discussed. In section 5, we explore the potential of refining single-view-angle retrieval by using multi-angle retrieval as a priori. On such a basis, the multi-angle view images of a targeted plume are retrieved independently, allowing temporal variation in the smoke particles from a wildfire plume during the short period of multi-angle acquisition. A short summary and outlook are provided in Section 6.

2. General structure of the inversion algorithm

The first version of aerosol retrieval adopted by AirMSPI is optimization-based. The Markov chain radiative transfer (RT) approach coupled with the adding-doubling method (MarCh-AD) is used as its forward model. To constrain aerosol properties, the MAP measurements are used in conjunction with the smoothness constraints across neighboring pixels, assuming that aerosol properties have a smooth variation in the horizontal dimension (Dubovik et al., 2011). The algorithm was validated using 27 datasets from several field campaigns, covering low to moderate aerosol loadings (AOD at 555 nm < 0.5) (Xu et al., 2017). These cases generally represented spatially homogeneous aerosol conditions. When applied to FIREX-AQ campaign data, the retrieval includes the following stages (see Fig. 1 for a flowchart):

1. **Preprocessing:** Average $p \times q$ of native-resolution pixels into retrieval superpixels, and screen out superpixels that violate certain metrics (e.g., ice/snow surfaces, ephemeral water, bright surfaces).
2. **Stage 1 — Independent Patch Retrieval:** Segment an image into patches of $m \times n$ aggregated superpixels and perform the optimization-based retrieval over each patch independently.
3. **Stage 2 — Cross-Patch Refinement:** Imposing additional smoothness constraints across-patch boundaries to refine the retrieval.

Stage 2 represents an upgrade of the existing AirMSPI algorithm, as described in Section 2.2. A further key novelty of this study is the replacement of the MarCh-AD radiative transfer model with a neural-network-based radiative transfer (NN-RT) model, which significantly improves the retrieval efficiency (cf. Section 2.3).

2.1. Optimization-based multi-pixel retrieval

Fig. 2 illustrates the diagram of the Stage-1 aerosol retrieval

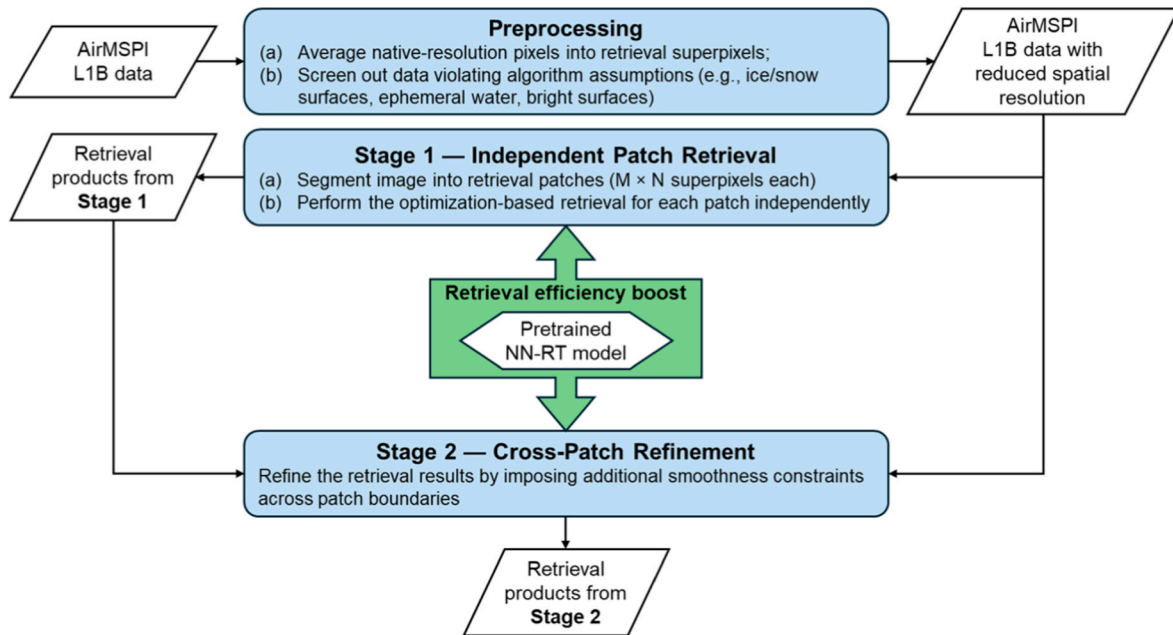


Fig. 1. The two-stage optimization-based aerosol retrieval applied to the FIREX-AQ campaign data acquired by AirMSPI.

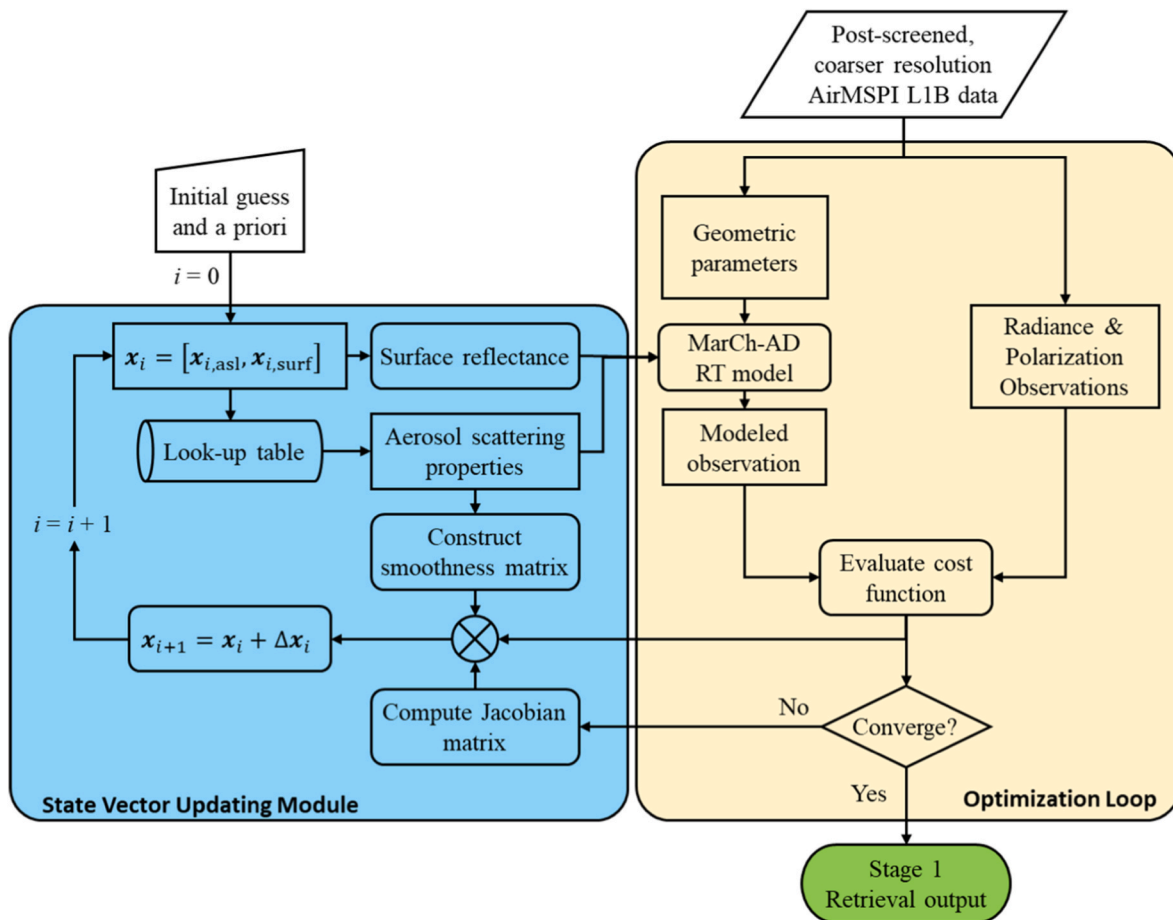


Fig. 2. Diagram of the optimization-based aerosol and surface property inversion (Stage-1 optimization).

algorithm. The state vector $\mathbf{x}$ consists of both aerosol properties $\mathbf{x}_{\text{asl}}$ and surface reflection parameters $\mathbf{x}_{\text{surf}}$, such that $\mathbf{x} = [\mathbf{x}_{\text{asl}}, \mathbf{x}_{\text{surf}}]$. The aerosol component includes parameters such as volume concentration, size

distribution, complex refractive index, and the fraction of nonspherical (spheroid) particles. These inputs are used to calculate light-scattering properties, including AOD, single-scattering albedo (SSA), and the

phase matrix. Together with parameters describing the depolarizing bidirectional reflectance distribution function (BRDF) and the polarized BRDF, the NN-RT surrogate model of the MarCh-AD RT is employed to compute the radiance field at the AirMSPI sensor altitude. The radiance field consists of the total radiance L and the normalized linear polarimetric components q and u , which are related to the Stokes vector components Q and U by $q = Q/L$ and $u = U/L$, respectively. The retrieval is formulated as an optimization problem, where the cost function quantifies the mismatch between measured and modeled radiances and linear polarimetric signals (L, q, u), while also incorporating smoothness constraints across spectral bands and spatial neighborhoods. At each iteration, the Jacobian matrix is computed with respect to the current state vector to guide the parameter updates. The step length is determined by evaluating the cost function gradient, and the state vector is updated accordingly. This iterative process continues until convergence, defined as the point at which the difference in the cost function between two successive iterations falls below a prescribed threshold.

2.2. Mitigation of quilting effect

In our optimization-based retrieval framework, the physical constraint of smooth spatial variations in aerosol parameters is capitalized on to stabilize the inversion (Dubovik et al., 2011; Xu et al., 2017). Ideally, all superpixels within a single observation scenario would be retrieved simultaneously, thereby fully exploiting the spatial smoothness constraints. However, this is impractical because it requires processing thousands of superpixels simultaneously and challenges computer memory. To alleviate the computational burden, each AirMSPI image is segmented into patches of $m \times n$ superpixels, which are retrieved independently using a multi-pixel inversion approach. This strategy, however, leads to a “disconnection” of retrieved solutions across two neighboring patches due to the absence of cross-patch constraints. Consequently, a “quilting effect” across the edges of neighboring patches can be observed, as indicated in Fig. 4a. While the quilting effect is a generic feature when multi-superpixel optimization-based retrievals are applied to independent patches, it becomes more pronounced in dense smoke scenes, due to stronger aerosol-surface coupling and increased spatial gradients of smoke distribution, both amplifying the sensitivity to cross-patch inconsistencies. To mitigate the quilting effect while preserving numerical tractability, within Stage 2 we adopt a multi-step retrieval strategy based on Dubovik et al. (2011). As illustrated in Fig. 3, the multi-step retrieval strategy proceeds in three steps:

1. Step 1 (blue patches labeled “1”): Each patch is retrieved independently and in parallel, providing the initial solutions.

2. Step 2 (orange patches labeled “2”): Smoothness constraints are imposed across neighboring patches by using the solutions of the boundary superpixels from Step 1 as a priori information.
3. Step 3 (green patches labeled “3”): The retrieval is refined over the same patches as in Step 1, with the solutions of the boundary superpixels from Step 2 serving as a priori information to enforce cross-patch smoothness.

The mathematical formulation of smoothness constraints across neighboring patches, used as a priori information, is well described in Appendix B of Dubovik et al. (2011). While Steps 2 and 3 could in principle be repeated to further enhance spatial smoothness, in this study three steps are applied, after which the retrieved state vectors for all superpixels already reflect spatial smoothness relationships both within and across patches. To demonstrate the effectiveness of the multi-step retrieval, we apply the approach to an AirMSPI observation of a wildfire event during the FIREX-AQ campaign. The retrieved AOD maps for this case (Fig. 4) illustrate the benefits of the multi-step approach. When all patches are retrieved independently, a noticeable quilting effect across patches appears in Fig. 4a. The observed mitigation of across-patch AOD discontinuities demonstrates the effectiveness of three-step retrieval. The major mitigation of the discontinuities is achieved by Step 2 retrieval. Step-3 retrieval provides further refinement, indicating the convergence of the three-step retrieval strategy.

It is important to note that the proposed strategy not only reduces quilting artifacts but also enhances the retrieval performance, as enforcing smooth transitions across patch boundaries is physically meaningful. In doing so, it further exploits the spatial smoothness of aerosol and surface parameters, helping to mitigate localized optimization artifacts. However, the three-step approach increases computational costs by approximately 50%. To address this limitation, we introduce a neural-network-based RT model in the next section.

2.3. Neural network trained radiative transfer calculation

Traditional optimization-based retrieval is computationally demanding, primarily because radiative transfer calculations must be repeated many times to fit the measured data. In iterative optimization, the Jacobian matrix is required to determine the direction and step size for updating the state vector, which further increases the computational load when using conventional finite-difference methods.

To expedite retrieval, this study adopts a neural-network-based radiative transfer (NN-RT) model as an approximation of the physical RT model to calculate the Stokes vector components. A dataset that contains a large number of training samples is generated using the Markov chain RT model. Once trained, the Jacobian matrix is obtained

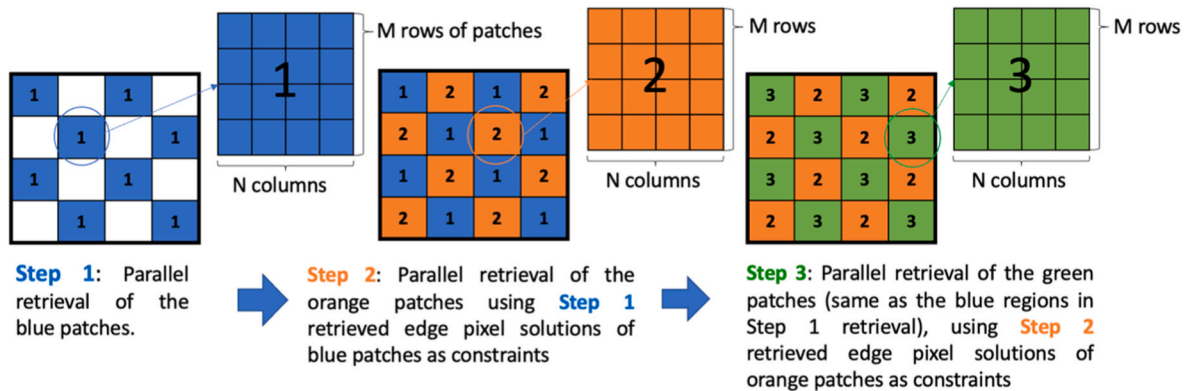


Fig. 3. Illustration of the multi-step retrieval strategy aimed at mitigating the “quilting” effect across patches. The patches marked with the numbers “1” and “2” represent distinct groups of patches involved in Step 1 and 2 retrievals, each encompassing $m \times n$ superpixels. The green patches marked with the number 3 are same as the blue patches marked with number “2”. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

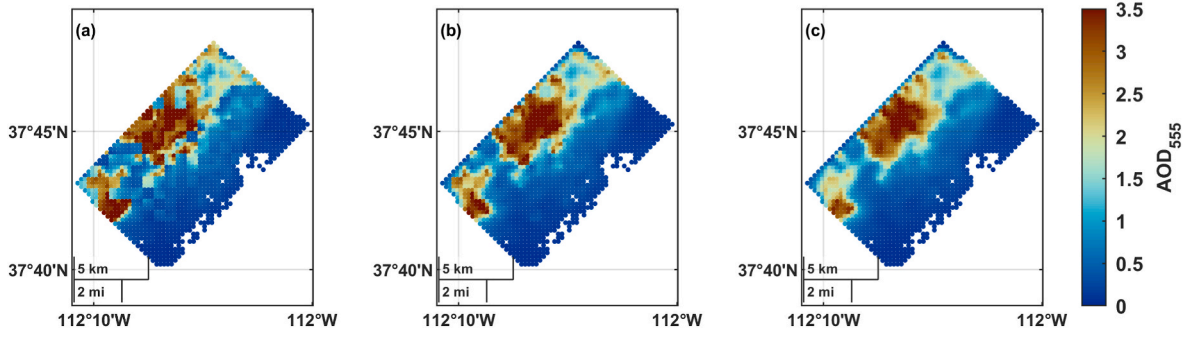


Fig. 4. AOD retrieved from AirMSPI using (a) independent retrieval of all patched at one time; (b) two-step retrieval to mitigate the quilting effect. (c) three-step retrieval to achieve convergence.

analytically from the output NN-RT model coefficients, thus improving computational efficiency, as demonstrated in Section 2.3.3.

2.3.1. Training data

To train the NN-RT model, radiative transfer simulations are first performed for many random combinations of state vector parameters, including solar and viewing geometries covering diverse aerosol and surface scenarios. This produces a large dataset containing radiance and polarimetric components. In this study, 1.6 million cases were simulated for each AirMSPI band, of which 1.5 million cases were randomly selected for training, and the remaining 0.1 million cases were reserved for accuracy assessment, as discussed in Section 2.3.2. Using the same approach, light scattering calculations are trained using random combinations of aerosol properties $\mathbf{x}_{\text{asl}}$ to predict light scattering properties, including AOD, SSA, and phase matrix.

To ensure adequate representation, the state vector parameters are sampled over reasonable parameter ranges when preparing the radiative transfer simulations. While some variables span wide ranges, most real-world scenarios occupy a narrower subset. To account for this, certain parameters are sampled from a linear distribution, while others are sampled from a log-uniform distribution to better reflect their observed distributions. For variables whose ranges do not align well with direct log-uniform sampling, an offset is added before sampling and subtracted afterward, ensuring a closer match to observed data patterns. The ranges and corresponding sampling strategies are summarized in Table 1.

2.3.2. Neural network training

A feed-forward neural network implemented in MATLAB is used to train both the light-scattering and radiative transfer models. As shown in Fig. 5, the architecture consists of one input layer, p fully connected hidden layers ($\mathbf{h}$), and one linear output layer. The input layer transforms the state vector $\mathbf{x}$, which drives the forward model, into the first hidden layer vector $\mathbf{h}_1$:

$$\mathbf{h}_1 = \Phi_1(\mathbf{W}_1^T \mathbf{x} + \mathbf{b}_1), \quad (1)$$

where $\mathbf{W}_1$ and $\mathbf{b}_1$ input layer's weight matrix and bias vector, and Φ_1 is its activation function. For the k -th hidden layer, the mapping is given by

$$\mathbf{h}_{k+1} = \Phi_k(\mathbf{W}_k^T \mathbf{h}_k + \mathbf{b}_k), k = 1, \dots, p, \quad (2)$$

with $\mathbf{W}_k$ and $\mathbf{b}_k$ being the weight matrix and bias vector of the corresponding hidden layer, and Φ_k is the associated activation function. Finally, the output layer performs a linear transformation of the last hidden layer vector $\mathbf{h}_p$ to the output vector $\mathbf{y}$:

$$\mathbf{y} = \mathbf{W}_o \mathbf{h}_p + \mathbf{b}_o. \quad (3)$$

Here, $\mathbf{y}$ represents either radiance and linear polarimetric components ($\mathbf{L}$, $\mathbf{q}$ and $\mathbf{u}$), or light scattering properties such as AOD and SSA.

Various activation functions were evaluated, and the hyperbolic tangent (Tanh) function was chosen for its smoothness and ability to

capture the nonlinear behavior of the trained functions:

$$\tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}. \quad (4)$$

For radiative transfer modeling, the neural network architecture consists of 7 hidden layers with 18 neurons each, while for aerosol single-scattering calculations, 3 hidden layers with 18 neurons each are used. The training process aims to minimize the cost function, defined here as the mean square error (MSE) between the training data generated from radiative transfer or light scattering computations and the predicted neural network values. The selection of hyperparameters and architecture requires careful optimization. We choose the Levenberg-Marquardt algorithm as the optimizer, which provides efficient optimization during the backpropagation step.

After training, the performance of the neural-network-based radiative transfer and scattering models is evaluated using 0.1 million independent simulation cases per band that were not included in the training set. Fig. 6 compares neural-network predictions with direct model calculations for AOD, SSA, BRF, and the polarized component q at the 555 nm band. The models for aerosol properties (AOD and SSA) are highly accurate, with mean absolute errors at the order of 0.0001. For the radiative transfer outputs (BRF and q), the neural network reproduces the reference calculations with errors of less than 1% for BRF and about 0.01 for q , and the majority of neural network predictions fall within the expected measurement uncertainty of AirMSPI, as indicated by the light-green shading in Fig. 6. Based on this demonstrated accuracy, the NN-RT model is applied in the remainder of this study for AirMSPI FIREX-AQ data retrieval.

2.3.3. Jacobian matrix

The calculation of the Jacobian matrix is a key step in optimization-based retrieval. This matrix characterizes how a radiative field or scattering quantity responds to small perturbations in the elements of the state vector. It guides both the search direction and the step length toward the solution. For an observation vector comprising N measurements ($\mathbf{y} = [y_1, y_2, \dots, y_N]^T$) and a state vector of M components ($\mathbf{x} = [x_1, x_2, \dots, x_M]^T$), the Jacobian matrix is defined as:

$$\mathbf{J} = \begin{bmatrix} \frac{\partial y_1}{\partial x_1} & \frac{\partial y_1}{\partial x_2} & \dots & \frac{\partial y_1}{\partial x_M} \\ \frac{\partial y_2}{\partial x_1} & \frac{\partial y_2}{\partial x_2} & \dots & \frac{\partial y_2}{\partial x_M} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial y_N}{\partial x_1} & \frac{\partial y_N}{\partial x_2} & \dots & \frac{\partial y_N}{\partial x_M} \end{bmatrix}_{N \times M}. \quad (5)$$

In conventional approaches, the Jacobian is often evaluated using finite-difference method (FDM), in which the forward model is repeatedly rerun with perturbed state parameters (x_m):

Table 1

Parameter ranges and sampling strategies for aerosol and surface properties and solar-viewing geometry used in generating the radiative transfer and light-scattering datasets for neural network training.

Parameters	Symbol	Unit	Range	Sampling	Sampling offset
AEROSOL PROPERTIES					
Total aerosol volume concentration	C_v	$\mu\text{m}^3/\mu\text{m}^2$	[1e-6, 5]	log-uniform	1e-2
Volume fraction of fine mode aerosols	$f_{v, \text{fine}}$	-	[0.01, 0.99]	linear	-
Fine mode aerosol characteristic radius	$R_{\text{eff}, \text{fine}}$	μm	[0.08, 1.00]	log-uniform	0
Fine mode aerosol logarithmic characteristic width	$\ln S_{\text{fine}}$	-	[0.2, 0.6]	log-uniform	0
Coarse mode aerosol characteristic radius	$R_{\text{eff}, \text{coarse}}$	μm	[1, 10]	linear	-
Coarse mode aerosol logarithmic characteristic width	$\ln S_{\text{coarse}}$	-	[0.3, 0.5]	log-uniform	0
Aerosol effective layer height	H_{asl}	km	[0.05, 10]	log-uniform	0.5
Half width of aerosol layer	S_{asl}	km	[0.5, 2.5]	log-uniform	0
Real refractive index for fine mode aerosols	$m_{r, \text{fine}}$	-	[1.36, 1.60]	log-uniform	0
Imaginary refractive index for fine mode aerosols	$m_{i, \text{fine}}$	-	[4.9e-5, 0.1]	log-uniform	0
Real refractive index for coarse mode aerosols	$m_{r, \text{coarse}}$	-	[1.36, 1.60]	log-uniform	0
Imaginary refractive index for coarse mode aerosols	$m_{i, \text{coarse}}$	-	[4.9e-5, 0.1]	log-uniform	0
Spherical particle fraction	$f_{v, \text{spheric}}$	-	[0.05, 0.99]	linear	-
SURFACE PROPERTIES					
Spectral weight of BRDF	a_λ	-	[0.001, 1.00]	log-uniform	0
Anisotropy parameter 1	k_λ	-	[1e-3, 1.00]	log-uniform	1
Anisotropy parameter 2	g_λ	-	[-0.999, 0.999]	log-uniform	1
Weight of pBRDF	e_λ	-	[1e-3, 50]	log-uniform	0
Shadowing width	k_γ	-	[1, 100]	log-uniform	0
Slope variance	σ_s^2	-	[0.01, 1]	linear	-
Surface Altitude	Alt_{surf}	km	[0, 6]	log-uniform	1
SOLAR AND VIEWING GEOMETRIES					
Solar zenith angles	θ_0	$^\circ$	[0, 75]	linear	-
viewing zenith angles	θ_v	$^\circ$	[0, 75]	linear	-
relative viewing azimuth angle	ϕ_v	$^\circ$	[0, 360]	linear	-

$$\frac{\partial y_n}{\partial \mathbf{x}_m} = \frac{y_n(\mathbf{x}_1, \mathbf{x}_2, \dots, (\mathbf{x}_m + \Delta \mathbf{x}_m), \dots, \mathbf{x}_M) - y_n(\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_m, \dots, \mathbf{x}_M)}{\Delta \mathbf{x}_m} \quad (6)$$

While straightforward, this approach is computationally expensive for large state vectors. In NN-RT, the Jacobian can be derived analytically from the neural network coefficients using the chain rule (Baydin et al., 2018). The output layer is a linear connection layer, so the derivative of the network output y_n with respect to the input is:

$$\frac{\partial y_n}{\partial \mathbf{x}} = \mathbf{W}_o \frac{\partial \mathbf{h}_{p+1}}{\partial \mathbf{x}} \quad (7)$$

For a hidden layer k , the derivative of its activation with respect to the input is given by:

$$\frac{\partial \mathbf{h}_{k+1}}{\partial \mathbf{x}} = \frac{\partial \Phi_k(\mathbf{f}_k)}{\partial \mathbf{f}_k} \frac{\partial \mathbf{f}_k}{\partial \mathbf{x}} \quad (8)$$

where $\mathbf{f}_k$ is the pre-activation input of the layer, and the derivative of $\mathbf{f}_k$ with respect to the input can be expressed recursively as:

$$\frac{\partial \mathbf{f}_k}{\partial \mathbf{x}} = \mathbf{W}_k^T \frac{\partial \mathbf{h}_k}{\partial \mathbf{x}}, k = 1, \dots, p. \quad (9)$$

And for the adopted hyperbolic tangent activation function, the derivative with respect to $\mathbf{f}_k$ is

$$\frac{\partial \Phi_k(\mathbf{f}_k)}{\partial \mathbf{f}_k} = 1 - \tanh^2(\mathbf{f}_k) = 1 - \mathbf{h}_{k+1}^2. \quad (10)$$

Together, these relations provide a recursive formulation for computing the Jacobian matrix analytically from the trained NN-RT model. The analytical calculation of Jacobian is a key methodological advantage of the NN-RT approach. It enables stable and efficient aerosol retrieval and avoids the disadvantage of FDM in properly perturbing each state vector parameter and re-run the RT model to get the relevant derivative.

To evaluate the accuracy of the Jacobian matrix computed from the NN-RT model, we compared the metric elements against those derived from the physical RT model using FDM. Specifically, we chose 50 state vectors containing random combinations of retrieval parameters and perturbed them with a step size of 0.01. The FDM and physical RT model based calculation of Jacobians were compared with the analytical Jacobians obtained from the NN-RT model. The scatter plot in Fig. 7a shows a direct comparison of all Jacobian elements from the two approaches through regression. Each color corresponds to a specific state vector sample. Overall, the NN-RT Jacobians agree well with the physical RT results, with a regression slope close to unity (0.973), a correlation coefficient of 0.993, and a small mean absolute difference (MAD = 0.008).

To examine state-vector-parameter-dependent Jacobian differences, Fig. 7b shows the mean difference between the NN-RT-based and physical-RT-plus-FDM-based Jacobians. The overall discrepancies are relatively small for most parameters, confirming that the NN-RT model provides a reliable approximation for Jacobian calculation. Relatively larger discrepancies are found at a few viewing angles with respect to the real part of the aerosol refractive index. However, the magnitude and sign of the physical-RT- and NN-RT-based Jacobians, which dominate the direction of the solution search, remain consistent in most cases. When multiple viewing angles are used jointly, the optimal solution can still be successfully found after a few iterations.

2.3.4. Efficiency

By employing neural networks to compute scattering properties and radiative fields, aerosol retrieval is significantly accelerated. For example, a three-step retrieval applied to five patches (each patch composed of 3×3 superpixels) executed on a desktop computer with an Intel i9-12900K CPU and 32 GB RAM achieves a retrieval speed of approximately 0.4 s per pixel. This represents a two-order-of-magnitude speedup over retrievals that rely on online radiative transfer and scattering models, enabling near-real-time aerosol retrievals from AirMSPI data.

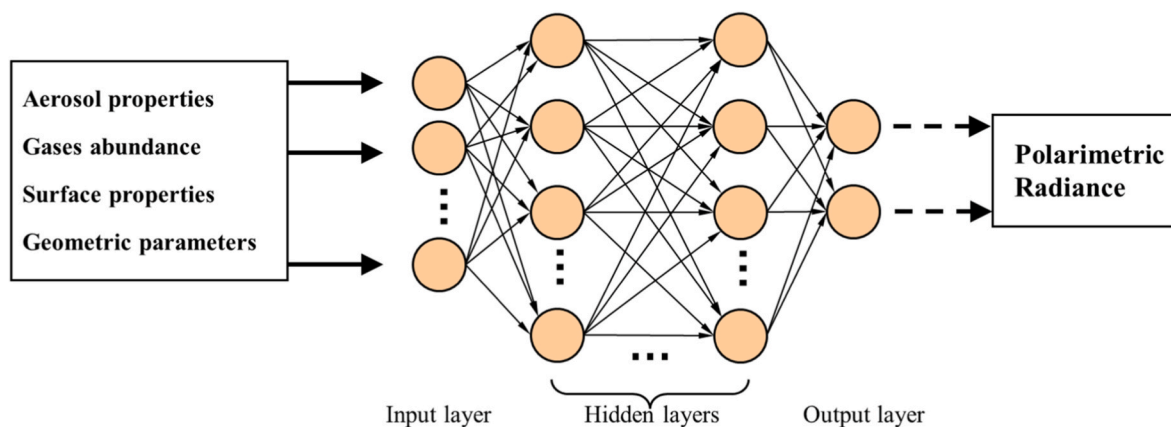


Fig. 5. Schematic diagram of a neural network for polarimetric radiance in the right box. The left box indicates the input parameters including aerosol properties, surface reflection properties, sun-illumination and view geometries and surface elevation.

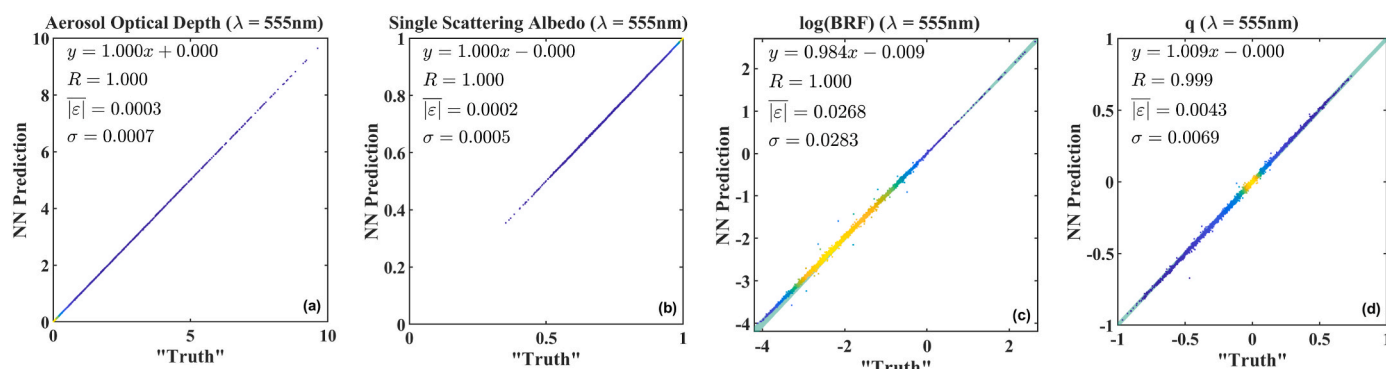


Fig. 6. Comparison of neural-network predictions with direct model calculations for AOD, SSA, intensity (in BRF unit) and polarimetric component q at 555 nm band to their directly calculated values. The light-green shading represents the AirMSPI measurement uncertainty. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

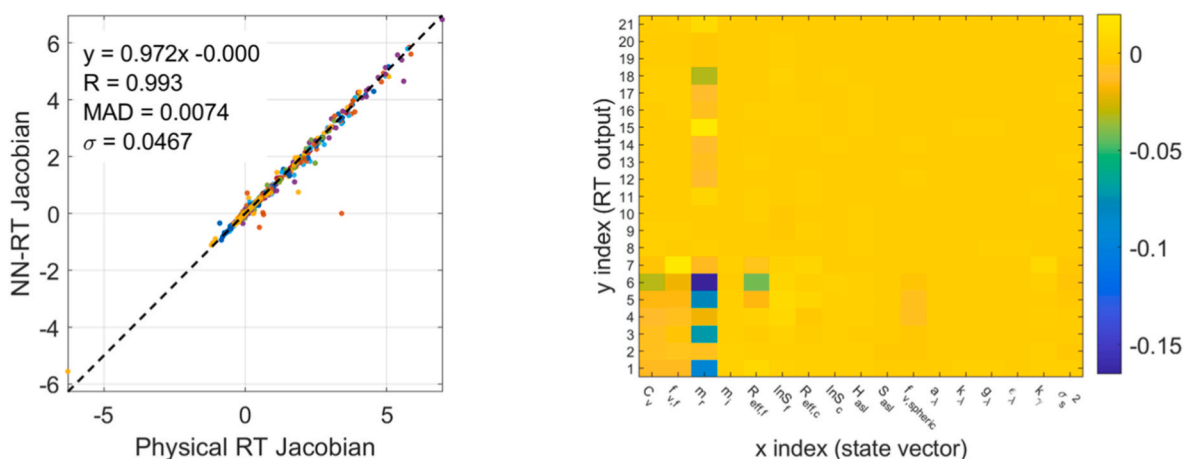


Fig. 7. Comparison between Jacobians calculated from the neural-network radiative transfer (NN-RT) model and those from the physical radiative transfer model using the finite-difference method (FDM). A total of 50 randomly assembled state vectors were used. (a) Direct comparison in a scattered plot. (b) Mean absolute difference of Jacobian with respect to all state vector parameters calculated using the two approaches.

3. Data

3.1. AirMSPI

AirMSPI is an eight-band (355, 380, 445, 470, 555, 660, 865, 935 nm) pushbroom camera mounted on a gimbal. Polarimetric

measurements of (BRF, q , u) are made at 470, 660, and 865 nm bands. Multiangular observations are acquired over a $\pm 67^\circ$ along-track angular range. AirMSPI operates in two modes: (1) “step and stare” mode, providing up to nine viewing angles’ measurement at ~ 10 m native spatial resolution, and (2) “continuous sweep” mode, with ~ 25 m spatial resolution (Diner et al., 2013). For aerosol property research, the

step-and-stare mode is preferred due to its higher spatial resolution and multi-view angular observations of a targeted area, which offers valuable information to constrain aerosol properties. During the FIREX-AQ campaign, AirMSPI was installed in the nose of a NASA ER-2 aircraft, and a total of 118 scenarios were acquired using step-and-stare view mode. They are numbered from Case 1 to 118 in this study.

In the FIREX-AQ campaign, AirMSPI “views” a scenario using five or nine viewing angles, symmetric around the nadir (0°). As illustrated in Fig. 8, in the case of nine angular views, including the nadir view (0°) and off-nadir views at $\pm 27.4^\circ$, $\pm 45.8^\circ$, $\pm 57.1^\circ$, and $\pm 64.5^\circ$. The nine viewing angles are labeled in this study as View 1 through View 9, arranged from the most forward-looking to the most backward-looking direction. Positive angles denote forward-looking directions, whereas negative angles denote backward-looking directions. For the five angular view case, measurements were taken at angles 0° , $\pm 46.7^\circ$, and $\pm 64.6^\circ$, namely View 1, 3, 5, 7, and 9 of the nine-angle case.

AirMSPI resolves a scenario with high spatial resolution of 10 m, offering valuable insights into cloud and landform properties (Diner et al., 2005a, 2005b; King et al., 1999). For aerosol retrieval, however, the plane-parallel radiative transfer assumption at such a fine scale is subjected to modeling errors (Marshak and Davis, 2005). They also challenge most bidirectional reflectance distribution function (BRDF) models which lack adaptability to fine-scale surface variability. To mitigate these challenges, we aggregated 25×25 pixels into a “super-pixel” of 250m spatial resolution.

3.2. The aerosol robotic network (AERONET)

AERONET provides AOD with well-characterized uncertainties of ~ 0.01 in the visible and near-infrared wavelengths and ~ 0.02 in the ultraviolet (UV) channels (340 and 380 nm) (Giles et al., 2019), and serves as a ground-truth reference for satellite and airborne remote sensing instruments.

For the FIREX-AQ campaign, two types of AERONET data are available: conventional and Distributed Regional Aerosol Gridded Observation Networks (DRAGON). Two DRAGON mobile teams deployed vehicle-mounted sun photometers to track fire events, in some cases approximately following the ER-2 flight tracks. However, there are

no DRAGON measurements overlapping spatiotemporally with AirMSPI observation, only Level 2.0 data from stationary AERONET sites are used for comparison.

For an AERONET site located within the spatial domain of an AirMSPI observation scenario, the superpixel whose center is geographically closest to the site is selected for analysis. Because AirMSPI uses a “step-and-stare” mode, each superpixel is observed multiple times from different viewing angles. AERONET measurements acquired within ± 15 min of the superpixel’s temporal span are considered collocated and used for comparison analysis.

3.3. The enhanced-MODIS airborne simulator (eMAS)

The eMAS is an airborne cross-track scanning spectrometer that provides MODIS-like observations but at substantially finer spatial resolution (e.g. 50m at an altitude of 20 km). It operates across 38 spectral channels spanning wavelengths from 0.445 to 13.844 μm . During the FIREX-AQ campaign, eMAS and AirMSPI were both deployed aboard the NASA ER-2 aircraft, enabling collocated spatial and temporal collocations for intercomparison.

Compared to AirMSPI’s 10 km swath at nadir, eMAS samples a much larger spatial domain (37.25 km wide swath at 20 km altitude), enabling more collocations with the ground-based AERONET and DRAGON measurements during the campaign. The eMAS AOD products from the FIREX-AQ campaign are derived using the Dark Target (DT) algorithm (Levy et al., 2013; Spencer et al., 2019) and have been extensively compared with the ground-based measurements (Shi et al., 2024). Given the limited number of AirMSPI-ground matchups, eMAS aerosol retrievals are used as an independent airborne reference to evaluate AirMSPI AOD retrievals, with due consideration of the uncertainties and assumptions inherent in both algorithms.

3.4. The cloud physics lidar (CPL)

The Cloud Physics Lidar (CPL; McGill et al., 2002) is a nadir-viewing elastic backscatter lidar flown on NASA’s ER-2 aircraft. It operates at three wavelengths (355, 532, and 1064 nm) and provides high-resolution vertical profiles of atmospheric backscatter and

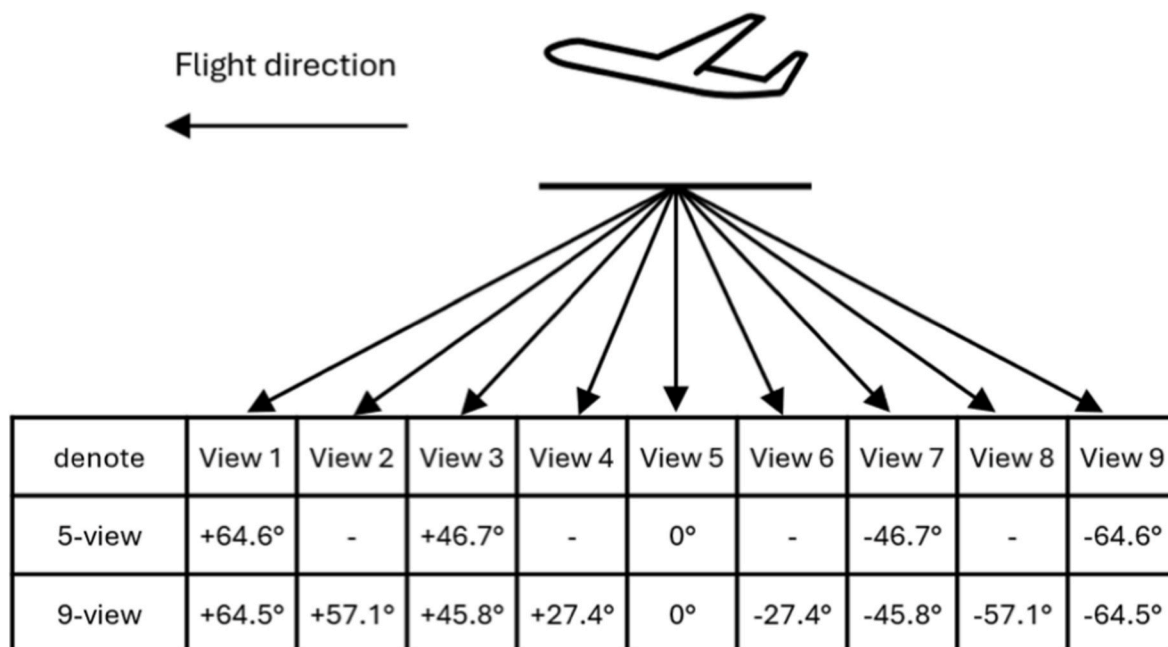


Fig. 8. AirMSPI’s five- and nine-angle step-and-stare view of a scenario. Positive angles denote forward-looking directions, negative angles denote backward-looking directions, and 0° denote nadir view.

extinction. CPL has a vertical resolution of 30 m and a horizontal resolution of ~ 200 m, making it well suited for resolving the vertical structure of aerosol and cloud layers. In this study, we use collocated CPL extinction profiles at 532 nm as reference data for evaluating the aerosol layer heights retrieved from AirMSPI.

4. Comparison of AOD retrieval

4.1. Comparison to AERONET reference AODs

Using the collocation criteria described in Section 3.2, three AirMSPI scenarios are identified as coinciding with AERONET observations. These collocated cases are characterized by relatively clear-sky conditions without pronounced plume heterogeneity. Consequently, AERONET comparisons in this work primarily serve as a consistency check under these conditions. The details of the cases are summarized in Table 2. For each case, all available viewing angles are used in the aerosol retrievals, as the aerosol fields are relatively homogeneous.

Fig. 9 compares the spectral AODs retrieved from AirMSPI with those from AERONET between 355 and 870 nm. For AERONET, the error bars represent the standard deviation of AODs collected within the AirMSPI overpass duration (~ 7 min) within a ± 15 min collocation window. Overall, the results show good consistency in both magnitude and spectral dependence, with differences generally within ~ 0.05 . This agreement demonstrates the capability of AirMSPI to retrieve reliable AODs under clear-sky conditions with the updated algorithm.

4.2. Comparison to eMAS reference AODs

Following the clear-sky validation of AirMSPI AODs against AERONET, we next examine their performance under smoky conditions. In this case, direct validation with AERONET or DRAGON is not available, as there are no collocated observations with AirMSPI. Instead, we perform an intercomparison with eMAS AODs, which have themselves been well validated against AERONET measurements in a recent study by Shi et al. (2024).

As an illustrative case, we analyze the Williams Flat Fire event on August 6, 2019 (Case 21), for which AirMSPI captured the scene with a nadir overpass at 18:39 UTC over Keller, Washington. This case was selected because the measurement domain is near the wildfire core and encompasses both smoke-affected and relatively clear regions. Fig. 10a shows the map of eMAS reported AOD at 550 nm (AOD_{550}), with the AirMSPI measurement area outlined in red and mobile DRAGON track marked as red dots. This highlights that the AirMSPI observation domain was positioned west of the main fire plume. The true-color image from AirMSPI's nadir view (Fig. 10b) reveals smoke in the northeastern portion of the scene, while the remainder appears relatively clear. Comparison of eMAS AODs against collocated mobile DRAGON measurements at 550 nm shows a reasonable agreement, as indicated in Fig. 10c. A zoomed-in view of the eMAS AOD_{550} map corresponding to the AirMSPI footprint is shown in Fig. 10d and 10e shows the map of AirMSPI AODs at 555 nm (AOD_{555}) retrieved from the five angular views (excluding the four most oblique views). The two maps exhibit similar spatial patterns of AODs, demonstrating the qualitative effectiveness of the algorithm in the presence of smoke. A pixel-to-pixel intercomparison of the two maps (Fig. 11c), together with the rationale for adopting the

five viewing angle configuration and its impact on retrieval behavior, is discussed in the following subsection.

When interpreting the AirMSPI-eMAS intercomparison, it is important to account for uncertainties arising from differences in the two instruments' spatial resolution and view geometry. AirMSPI retrieval resolves a relatively finer grid of a plume (namely 250m), whereas eMAS represents a spatially "averaged" aerosol retrieval over a relatively larger grid (namely 500m). This can cause differences in retrieval across regions with strong AOD variations. In addition, AirMSPI provides multiple views of a smoke plume but registers the multi-angular view images to the ground. In the presence of a 3D plume, this introduces differences in the sampled areas viewed from different viewing angles, further challenging the plane-parallel atmosphere assumption. In this context, the AirMSPI-eMAS retrieval comparison presented here should be interpreted qualitatively rather than as an absolute assessment of retrieval errors.

4.3. Impacts of viewing angle sampling on AOD retrieval

The applicability of plane-parallel model assumption in remote sensing of a plume scenario has been a concern, especially when observations were made at large off-nadir viewing angles. Although large view-angle enhances the sensitivity to a plume's heterogeneity and structure, it increases the errors of forward RT model based on plane-parallel atmosphere assumption. In this context, careful selection of viewing angles is needed to balance the information content and mitigation of the impact of the modeling error.

4.3.1. Impact of excluding extreme oblique views

To assess how extreme oblique views influence AOD retrieval performance, we conducted retrieval experiments using subsets of AirMSPI viewing angles, progressively removing the most oblique observations first, followed by less oblique views. The resulting AirMSPI AOD_{555} values were compared against eMAS AOD_{550} within the overlapping region (red box in Fig. 10a). Fig. 11a–e shows scatter plots comparing AirMSPI with eMAS AODs for different combinations of viewing angles: (a) 1–9, (b) 2–8, (c) 3–7, (d) 4–6, and (e) nadir only (View 5). Among the four multi-angle-based retrieval experiments, the retrieval using views 1–9 (Fig. 11a) is least accurate. This is because the two most oblique views ($\pm 65^\circ$) are more sensitive to 3-D plume structures, which increases the mismatch between the actual atmosphere and the plane-parallel assumption used in radiative transfer modeling. Excluding them leads to an improved agreement of AODs (Fig. 11b). Further excluding views at $\pm 57.1^\circ$ (5 angles, Fig. 11c) and then at $\pm 45.8^\circ$ (3 angles, Fig. 11d) yields even better performance. The 5-angle retrieval achieves the highest regression ($R = 0.73$), while the 3-angle retrieval gives the lowest bias (0.05) and RMSE (0.20). Compared to Fig. 11a and b, the 5-angle case shows a clear improvement in regression slope, whereas the 3-angle case reduces overestimation and produces tighter clustering around the 1:1 line for low to moderately high AODs. However, further reducing the retrieval to nadir-only measurements (Fig. 11e) substantially increases the AOD error. This is attributed to the limited information content provided by a single viewing angle, which is insufficient to constrain aerosol properties accurately.

Given AirMSPI's limited coverage of solar and viewing geometries during the FIREX-AQ campaign, it is challenging to identify an optimal

Table 2
Collocated AERONET–AirMSPI measurement during the FIREX-AQ campaign.

AirMSPI Scenario	AirMSPI Measurement UTC Time	Solar Zenith Angle	Number of Viewing Angle	AERONET Site	Number of Collocated Data Points
CA-MountainView, nadir, UTC 20:37, Aug 06, 2019	20:34 - 20:41	20.38°	9	NASA_Ames	4
CA-Pasadena, nadir, UTC 19:04, Aug 12, 2019	19:01 - 19:08	22.70°	9	CalTech	11
CA-Fresno, nadir, UTC 18:59, Aug 15, 2019	18:56 - 19:03	26.95°	5	Fresno_2	6

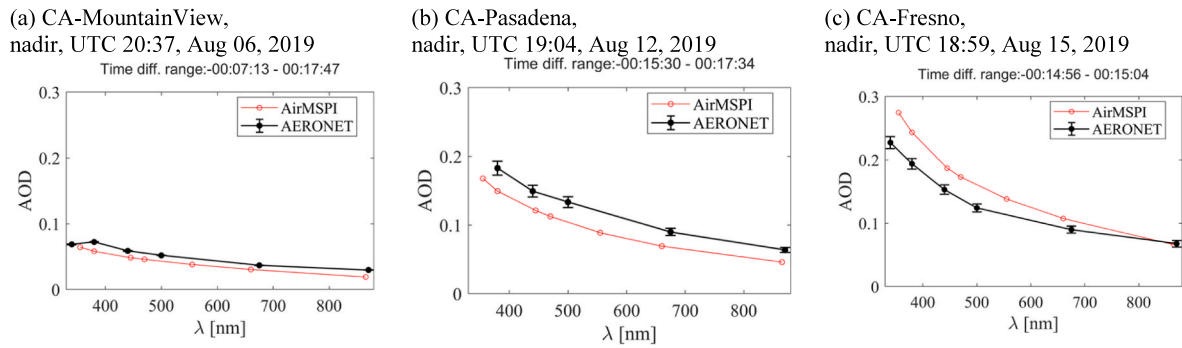


Fig. 9. Comparison of AirMSPI retrieved and AERONET reported AODs for (a) CA-MountainView UTC 20:37, Aug 06, 2019, (b) CA-Pasadena at UTC time 19:04 on Aug 12, 2019, and (c) CA-Fresno, UTC 18:59, Aug 15, 2019. Error bars with AERONET data represent the standard deviation of AOD with 15 min. The temporal difference ranges between AERONET and AirMSPI are shown in the titles of each subplot.

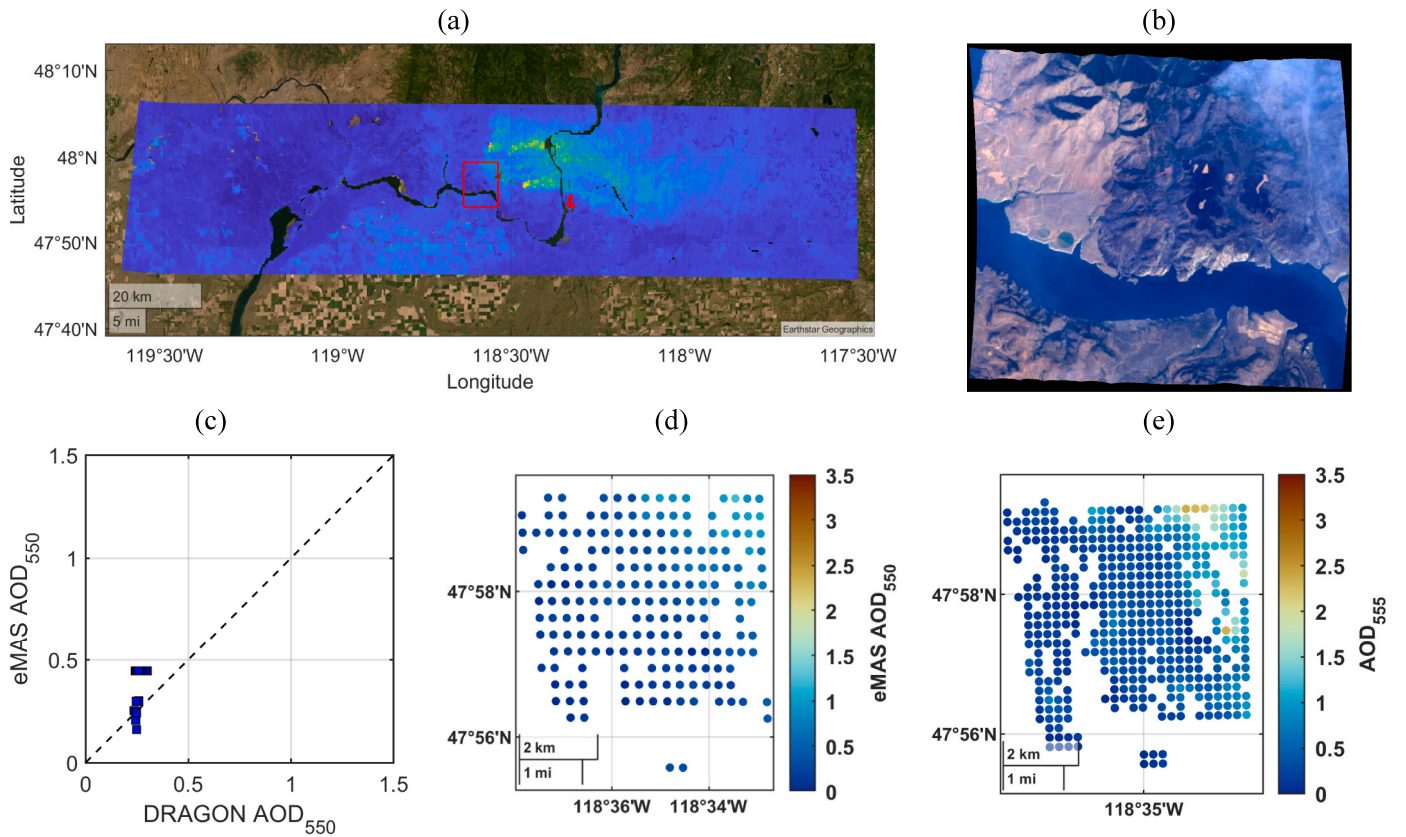


Fig. 10. Williams Flat Fire event over the city Keller of Washington which was captured by AirMSPI and eMAS at UTC time 18:39 on August 6, 2019. (a) The eMAS AOD map at 550 nm. The red rectangle denoting AirMSPI footprint and red dots showing mobile DRAGON track; (b) True color image of AirMSPI's nadir view; (c) Comparison of eMAS AODs against the collocated mobile DRAGON measurements at 550 nm; (d) Zoomed view of the eMAS AOD₅₅₀ map corresponding to the AirMSPI footprint; (e) AirMSPI AOD₅₅₅ map retrieved from the five angular views (excluding the four most oblique views). (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

number and locations of viewing angles that could work universally for plume retrieval. Nevertheless, our case study suggests that under moderately dense smoke conditions where the plume does not fully cover the scene, AOD retrievals from AirMSPI are improved when the two most oblique view-angle pairs are excluded from the original nine-view configuration. On such a basis, one can retain three to five viewing angles within $\pm 45.8^\circ$ of nadir to balance the mitigation of 3-D radiative effects and preserve a reasonable amount of information. Note that though eMAS has only a single viewing angle, its spectral coverage is larger than AirMSPI, which compensates for the lack of viewing angles, as revealed by the earlier study of [Hasekamp and Landgraf \(2007\)](#). By reducing the number of viewing angles to an optimal set, AirMSPI's

regional coverage and sampling frequency can be increased within a given number of flight hours, increasing the science return.

4.3.2. Sensitivity to angular sets within a fixed view angular range

The analysis in Section 4.3.1 suggests that, for smoke plume scenes observed by AirMSPI during the FIREX-AQ campaign, AOD retrievals can be improved by using three to five angles spanning approximately $\pm 57^\circ$ from nadir. Building on this result, we further investigate how retrieval stability depends on specific sets of viewing angles while keeping the overall viewing range constant. This analysis can help identify optimal viewing angles that provide higher retrieval sensitivity under the plane-parallel atmosphere assumption. Two AirMSPI cases

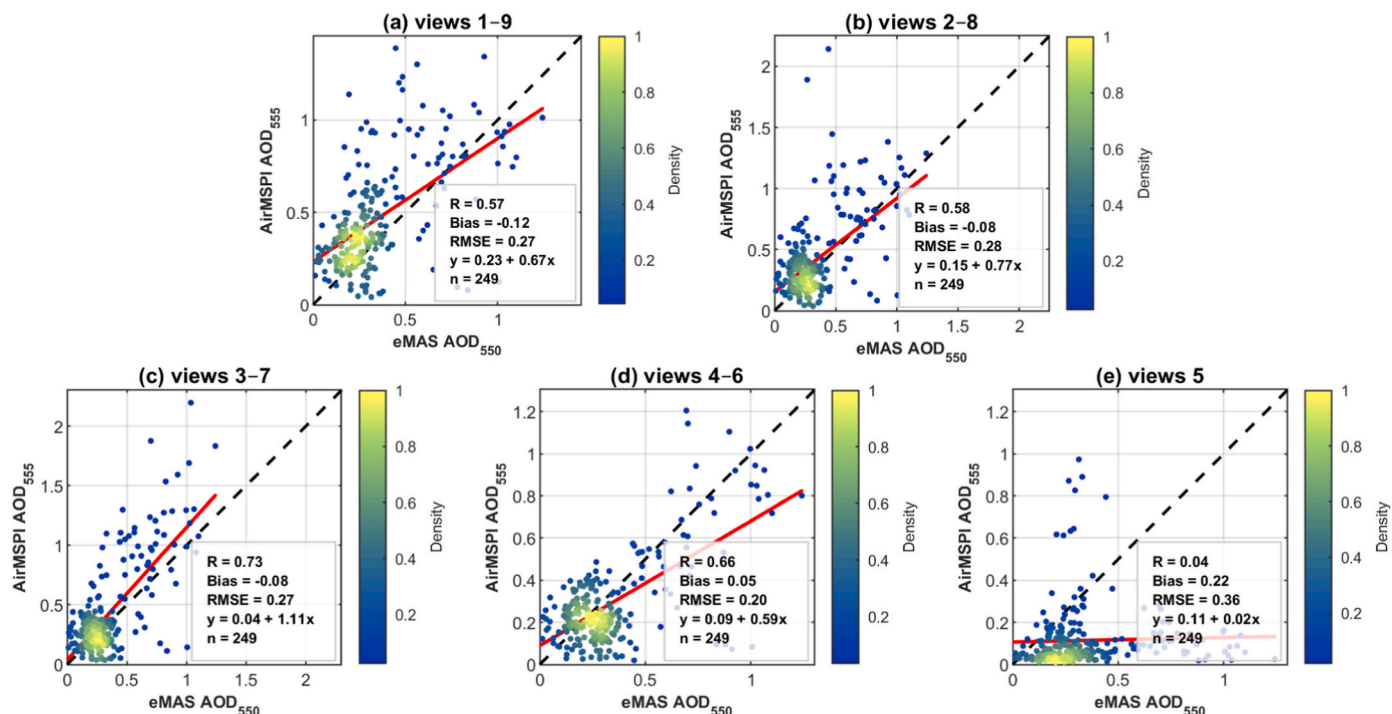


Fig. 11. Comparison of eMAS AOD₅₅₀ and AirMSPI AOD₅₅₅ retrieval using the measurements of the plume over city Keller at UTC time 18:39 on August 6, 2019. AirMSPI retrieval uses five different combinations of viewing angles. Panels (a)–(e) show scatter plots comparing AirMSPI AOD₅₅₅ retrieved using (a) 9 angles including nadir, $\pm 27.4^\circ$, $\pm 45.8^\circ$, $\pm 57.1^\circ$, and $\pm 64.5^\circ$ (b) 7 angles including nadir, $\pm 27.4^\circ$, $\pm 45.8^\circ$, and $\pm 57.1^\circ$ (c) 5 angles including nadir, $\pm 27.4^\circ$, and $\pm 45.8^\circ$ (d) 3 angles including nadir and $\pm 27.4^\circ$ and (e) single viewing angle (nadir).

with contrasting smoke densities are examined: including Case 21 which represents a relatively light smoke plume over Keller (see Fig. 9) and was discussed in the previous subsection, and Case 39 which corresponds to a denser smoke plume over Inchelium (see Fig. 12), captured at 20:28 UTC on August 7, 2019.

In these two cases, we compare AOD retrievals at five viewing angles (0° , $\pm 27.4^\circ$, $\pm 45.8^\circ$) with those at three angles (0° , $\pm 45.8^\circ$). Fig. 13 presents the results: the left and right scatter plots correspond to Case 21

and Case 39, respectively. While reducing the number of views from five to three yields only limited changes in the AODs of the light-smoke case, a noticeably larger spread emerges for the dense-smoke case, particularly in regions with AOD > 1. To examine the role of nadir observations in constraining multi-angle polarimetric AOD retrievals, Fig. 14 evaluates several reduced-viewing-angle configurations that exclude the nadir view while preserving the overall angular range (i.e., -45.8° to $+45.8^\circ$), using Case 21 as a testbed. Relative to the five-view retrieval (0° , $\pm 27.4^\circ$, and $\pm 45.8^\circ$), scatterplot comparisons reveal greater disagreement for the configurations that omit the nadir view than for the three-view configuration that retains the nadir view (0° and $\pm 45.8^\circ$). This result indicates that the information provided by nadir observations cannot be fully compensated for by off-nadir views, even when the overall angular coverage is preserved. This is probably because nadir observations of a targeted area violate the plane-parallel atmosphere assumption less than off-nadir observations. Moreover, nadir observations sample the atmospheric column directly, thereby providing a closer and more effective link to AOD, which is itself a column-integrated quantity.

Investigating the single-scattering phase function and polarization characteristics of smoke particles may provide further insight into our findings. Fig. 15 shows the phase function (P11) and degree of linear polarization (DOLP, $100 \times P_{12}/P_{11}$), with the corresponding parameters summarized in Table 3. The scattering angles corresponding to the viewing angles of Case 21 are marked by vertical lines in the plots. It can be found that the three-angle configuration captures the main features of the phase function and DOLP in the backscattering range. Therefore, reducing the number of views from five to three still preserves the critical angular information needed for retrievals of light-to-moderate smoke loading. For the dense smoke scenario (Case 39, Fig. 13b), however, reducing the number of viewing angles from five angles to fewer leads to increased retrieval variability. This is likely due to increased multiple scattering, which washes out the angular characteristics of single scattering. As a result, more angular information is needed to constrain aerosol properties under dense smoke conditions.

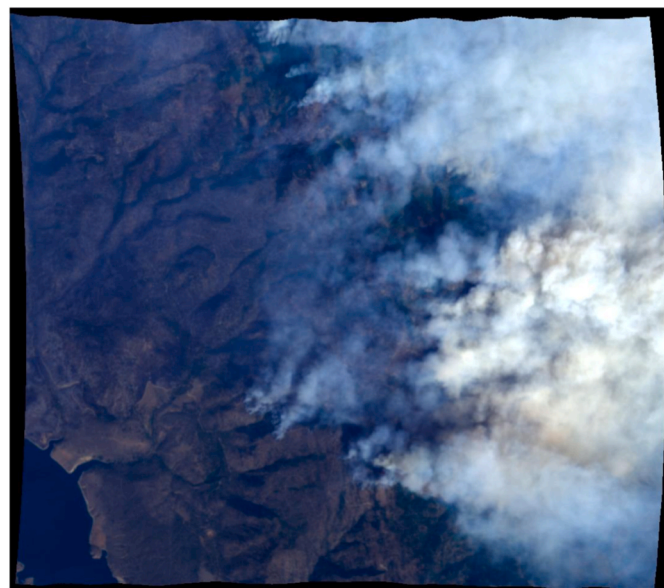


Fig. 12. True-color nadir image of the Williams Flat Fire over Inchelium, Washington, acquired by AirMSPI at 20:28 UTC on August 7, 2019. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

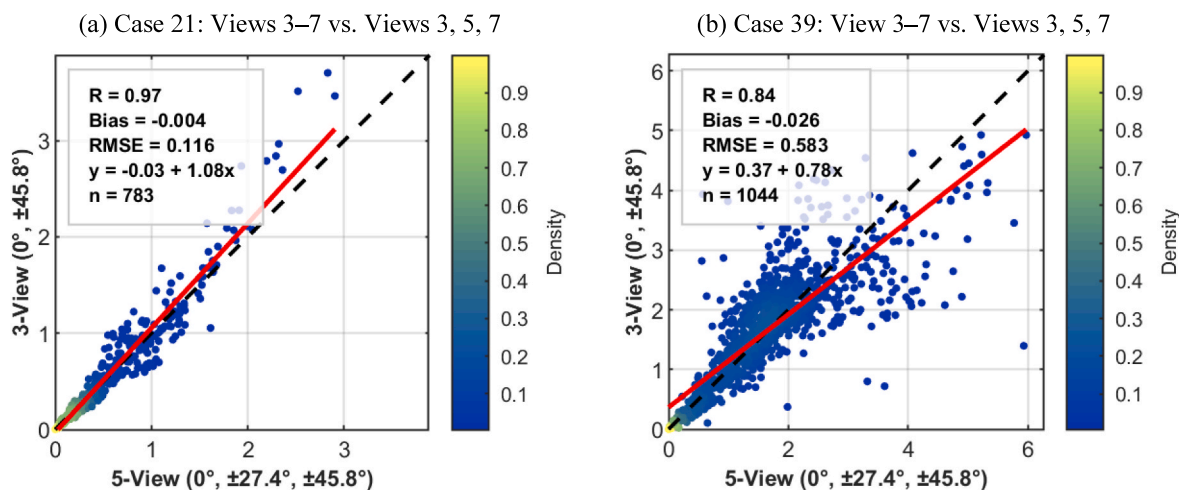


Fig. 13. Scatter plots comparing AirMSPI AOD₅₅₅ retrieved using 5- and 3- angle observation of the Williams Flat Fire. The left and right panels correspond to the scenarios acquired by AirMSPI at 18:39 UTC on August 6, 2019, and 20:28 UTC on August 7, 2019, respectively.

Overall, these results suggest that, for low to moderately high smoke particle loadings (e.g., AOD < ~2), using three viewing angles while keeping their angular range the same as that of five angles has a limited impact on AOD retrieval quality, as the main angular features are captured by the three angles. Nevertheless, the inclusion of the nadir view plays a critical role in stabilizing the inversion by providing an effective constraint on column-integrated aerosol loading. In contrast, for dense smoke plumes with high aerosol loadings (e.g., AOD > 2), retrieval accuracy becomes more sensitive to multiple scattering and having five viewing angles is helpful to improve aerosol retrieval.

5. More aerosol microphysics retrievals

5.1. Aerosol properties beyond AOD

In addition to AOD, AirMSPI retrieval also provides a set of aerosol microphysical properties such as size distributions and non-spherical particle fraction, the derived aerosol product such as SSA, as well as the aerosol layer location information such as the effective aerosol layer height (H_{asl}).

While reference data for validating AirMSPI-retrieved microphysical properties other than AOD are not available in this study, we use collocated CPL extinction profiles at 532 nm to evaluate the retrieved H_{asl} of smoke plumes. Case 39 is selected for demonstration since majority of the scene is covered with smoke plumes. Panel (a) of Fig. 16 shows the map of AirMSPI-retrieved H_{asl} , with an overlapped black line indicating the CPL flight trajectory. The black circles on the line mark the locations of collocated CPL measurements. Panel (b) shows the CPL extinction profile at 532 nm along the trajectory and the corresponding H_{asl} values retrieved from AirMSPI (in dots). Among the seven collocated data pairs, five H_{asl} values show reasonable agreement with CPL data, with differences of less than 1.5 km. Larger discrepancies by 2.5 and 3.5 km occur at the other two points, reflecting the uncertainties inherent in polarimetric retrievals of aerosol layer height.

5.2. Variations of smoke particle properties from single-view-angle retrieval

During a wildfire event, plumes are often elevated. In this context, each viewing angle of a multi-angle polarimeter samples a different part of the plume, and these sampled regions do not necessarily fully overlap. If an aerosol distribution is spatially uniform, one can assume same aerosols to be observed. However, this is not the case for plume retrieval as aerosol concentration and properties vary across the grids of a plume.

In addition, a plume evolves during a wildfire event and aerosol properties are expected to vary during AirMSPI's multi-angle acquisition period (e.g. ~4 min for acquiring 5 images) of a targeted area. Thus, a multi-angle retrieval effectively represents a spatially and temporally averaged solution. To gain insight into change in aerosol properties in coupled spatial and temporal scales, a single-view-angle aerosol retrieval is preferred. However, as shown in Section 4.2, single-view-angle retrievals suffer from large errors due to their limited information content. To address this, we conducted an additional experiment in which multiple-view retrieval results were used as initial guesses to inform single-view-angle retrievals. This approach allows the algorithm to begin optimization from a physically reasonable state derived from the multi-angle retrieval, thereby reducing the likelihood of getting locally optimized solutions. The results of such experiments on Case 21 are presented in Fig. 17. Panel (a) compares AirMSPI retrieved AOD₅₅₅ using five viewing angles (nadir, $\pm 27.4^\circ$, and $\pm 45.8^\circ$) with nadir-only retrievals informed by the five-view retrieval as the initial guess (hereafter referred to as “constrained nadir-only retrievals”). Overall, the informed nadir-only retrievals agree well with the five-view results, though some discrepancies remain. These differences arise because the nadir observation reflects the instantaneous aerosol state for the aerosol along the sight of view (plus some contamination of aerosols in neighboring grids through adjacency effect (Lyapustin and Kaufman, 2001)), whereas the multi-view retrieval represents a spatially and temporally averaged solution, potentially smoothing out the features that the nadir view captures. Panel (b) evaluates the benefit of this approach by comparing the informed nadir-only retrievals with eMAS AOD₅₅₀. These initialized retrievals show better agreement with the eMAS reference than does the nadir-only retrievals without initialization (see Fig. 11e), confirming that using multi-angle retrieval as an initial guess enhances the numerical stability and physical plausibility of single-view-angle retrievals.

Fig. 18 presents the retrieved aerosol properties, AOD₅₅₅, SSA at 555 nm (SSA₅₅₅), and fine mode aerosol characteristic radius ($R_{\text{eff, fine}}$), from five sequential single viewing angles over an approximately 4-min period. The aerosol microphysical properties (e.g., SSA₅₅₅ and $R_{\text{eff, fine}}$) are reported when AOD values at 445 nm are greater than 0.4. All single-view-angle retrieved aerosol quantities indicate strong correlations. The dense smoke plume, located in the northeastern portion of the scene, shows relatively higher AOD, higher SSA (>0.85), and larger fine-mode particle radii, which are physically consistent with expected plume evolution processes. This spatial structure is consistent with hygroscopic growth within the plume. Fresh smoke typically contains strongly light-absorbing components such as black carbon and brown carbon, which

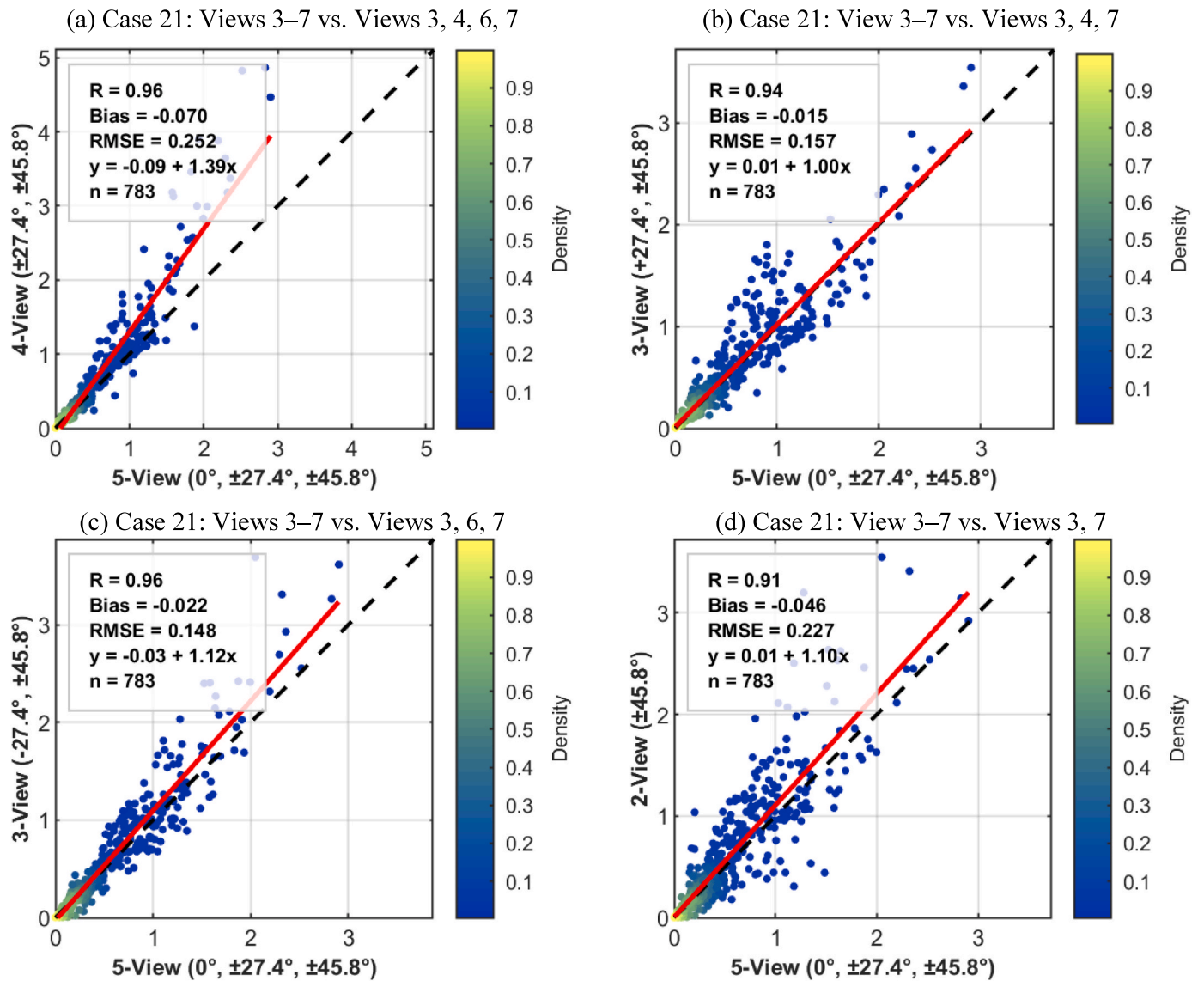


Fig. 14. Comparisons of AirMSPI AOD₅₅₅ retrievals using a reduced number (two to four) of viewing angles within the viewing angle range of $[-45.8^\circ, +45.8^\circ]$ with those using all five angles over the same angular range (namely views 3–7). The reduced-angle retrievals exclude the nadir view, but include: (a) views 3, 4, 6, and 7 ($\pm 27.4^\circ, \pm 45.8^\circ$); (b) views 3, 4, and 7 ($+27.4^\circ, \pm 45.8^\circ$); (c) views 3, 6, and 7 ($-27.4^\circ, \pm 45.8^\circ$); and (d) views 3 and 7 ($\pm 45.8^\circ$). The data is from the Williams Flat Fire acquired by AirMSPI at 18:39 UTC on August 6, 2019.

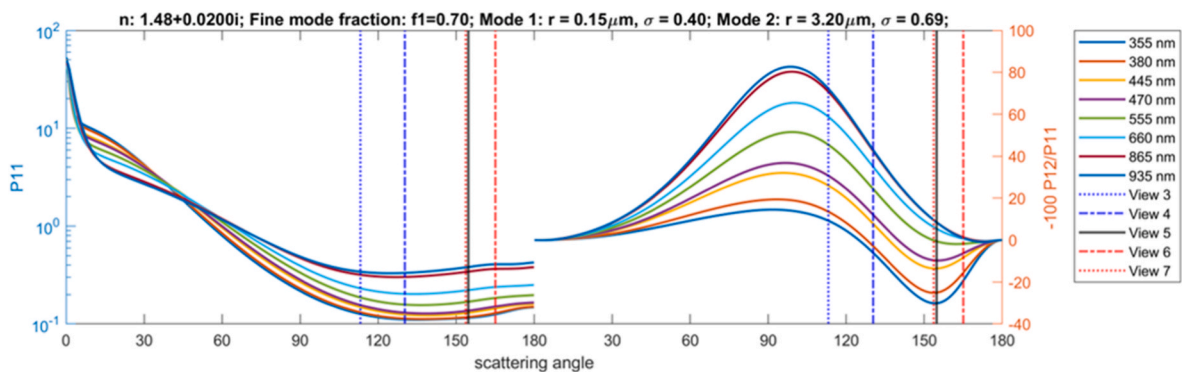


Fig. 15. Phase function (P_{11}) and degree of linear polarization ($-100 \times P_{12}/P_{11}$) by a representative smoke particle. Its parameters are summarized in Table 3. The dashed vertical lines indicate the corresponding scattering angles of the five views ($0^\circ, \pm 27.4^\circ, \pm 45.8^\circ$) from Case 21.

are associated with relatively low SSA values (0.74 ± 0.06 to 0.84 ± 0.06 ; Reid et al., 2005). As the plume ages and mixes with more

Table 3

Parameters of the smoke aerosols for single scattering calculation in Fig. 14.

Property	Value
Complex refractive index	$1.48 + 0.02i$
Size distribution	Bi-modal log-normal
Fine mode mean radius	$0.15 \mu\text{m}$
Fine mode logarithmic width	0.40
Coarse mode mean radius	$3.2 \mu\text{m}$
Coarse mode logarithmic width	0.69
Fine-mode volume fraction	0.7

humid air, water vapor condenses onto smoke particles, increasing particle size and enhancing light-scattering efficiency. In contrast, the lower SSA in the rest area may arise from the absence of conditions favorable for hygroscopic growth (i.e., lower humidity). Smoke particles diffusing into these drier regions are less likely to take up water and grow to increase SSA. This explains the lower AOD, lower SSA (0.80–0.85), and smaller particles observed in the rest of the imaged regions.

Comparison of the five single-view-angle retrievals indicates noticeable variations of the retrieval quantities, especially SSA_{555} and $R_{\text{eff, fine}}$. On one hand, the five-view images sample slightly different portions of the smoke plume. On the other hand, the plume itself may undergo physical and chemical changes during AirMSPI's multi-angle

imaging temporal window. In the absence of “ground-truth” observations, direct validation of these retrieval quantities is not feasible. Decoupling these variations into causes by viewing-angle dependent areas and by intrinsic plume evolution is also challenging. Despite these limitations, the results highlight several important implications. First, although multi-angle observation of a smoke plume offers more constraints, retrieval of smoke properties using all angle data may cause errors due to the assumptions of i) horizontal homogeneity of the scene in the traditional retrieval assumption of a plane-parallel atmosphere; and (ii) static smoke particle properties during a smoke plume event. Second, the potential of combining multi-angle-informed single-view-angle retrieval with a 3-D RT model (e.g. SHDOM, Evans, 1998) to assist with the capturing of temporal evolution and 3-D structure of aerosol microphysical properties of an actively developing smoke plume.

6. Summary and outlook

We developed a multi-step optimization-based inversion approach to retrieve smoke particle properties using polarimetric measurements. It ensures both the spatial continuity of retrieved aerosol parameters across adjacent image patches and the retrieval efficiency. The latter is achieved by using a Markov chain radiative transfer model trained with a neural network to further accelerate computation. This approach is

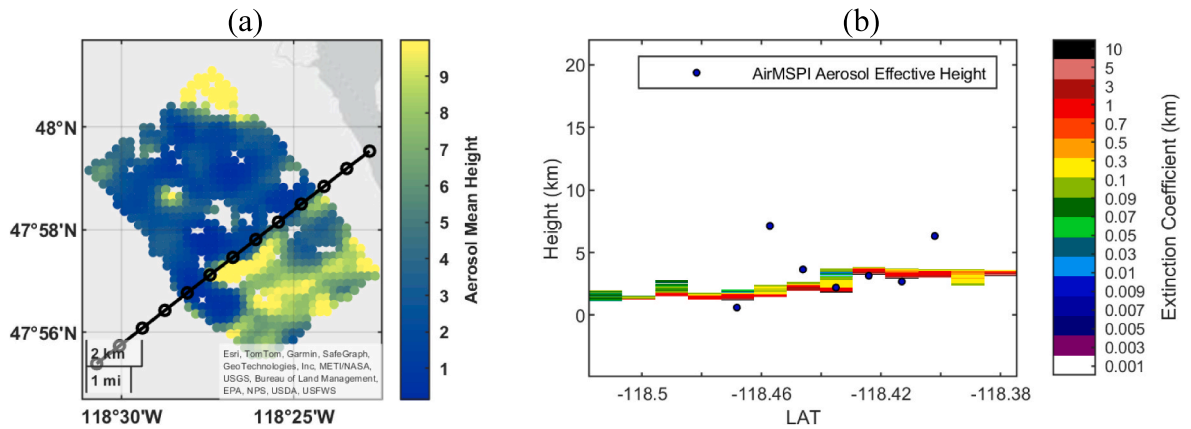


Fig. 16. (a) Map of AirMSPI retrieved aerosol effective layer height (H_{asl}) using 5-view observations ($0^\circ, \pm 27.4^\circ, \pm 45.8^\circ$) over Inchelium at 20:28 UTC on August 7, 2019. The black line indicates the CPL flight trajectory and black circles mark the location of collocated CPL data. (b) CPL extinction profile at 532 nm and comparison to AirMSPI retrievals of H_{asl} (blue dots). (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

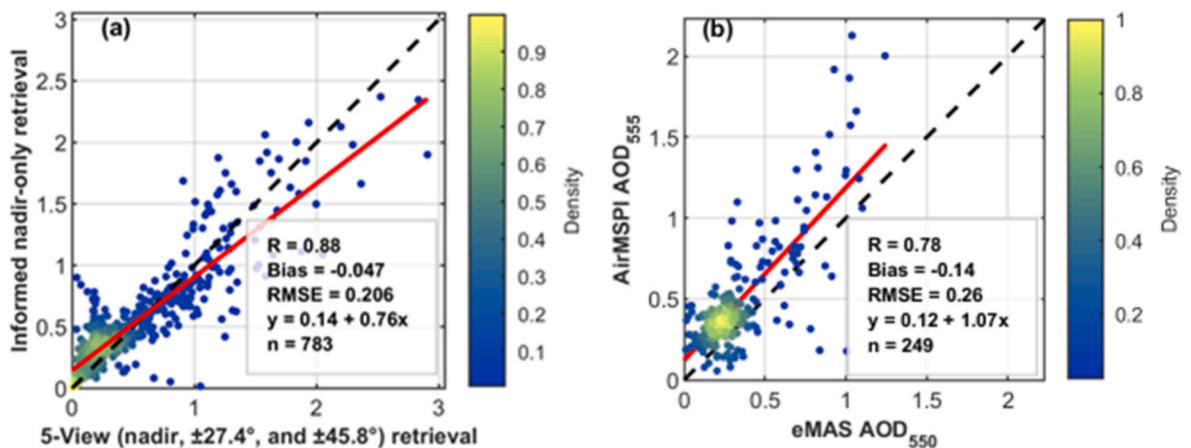


Fig. 17. (a) Comparison of AirMSPI AOD₅₅₅ from 5-view retrievals (nadir, $\pm 27.4^\circ, \pm 45.8^\circ$) with constrained nadir-only retrieval over city Keller. The nadir image was acquired at the UTC time 18:39 on August 6, 2019. (b) Comparison of informed nadir-only AOD₅₅₅ with eMAS AOD₅₅₀ reference data.

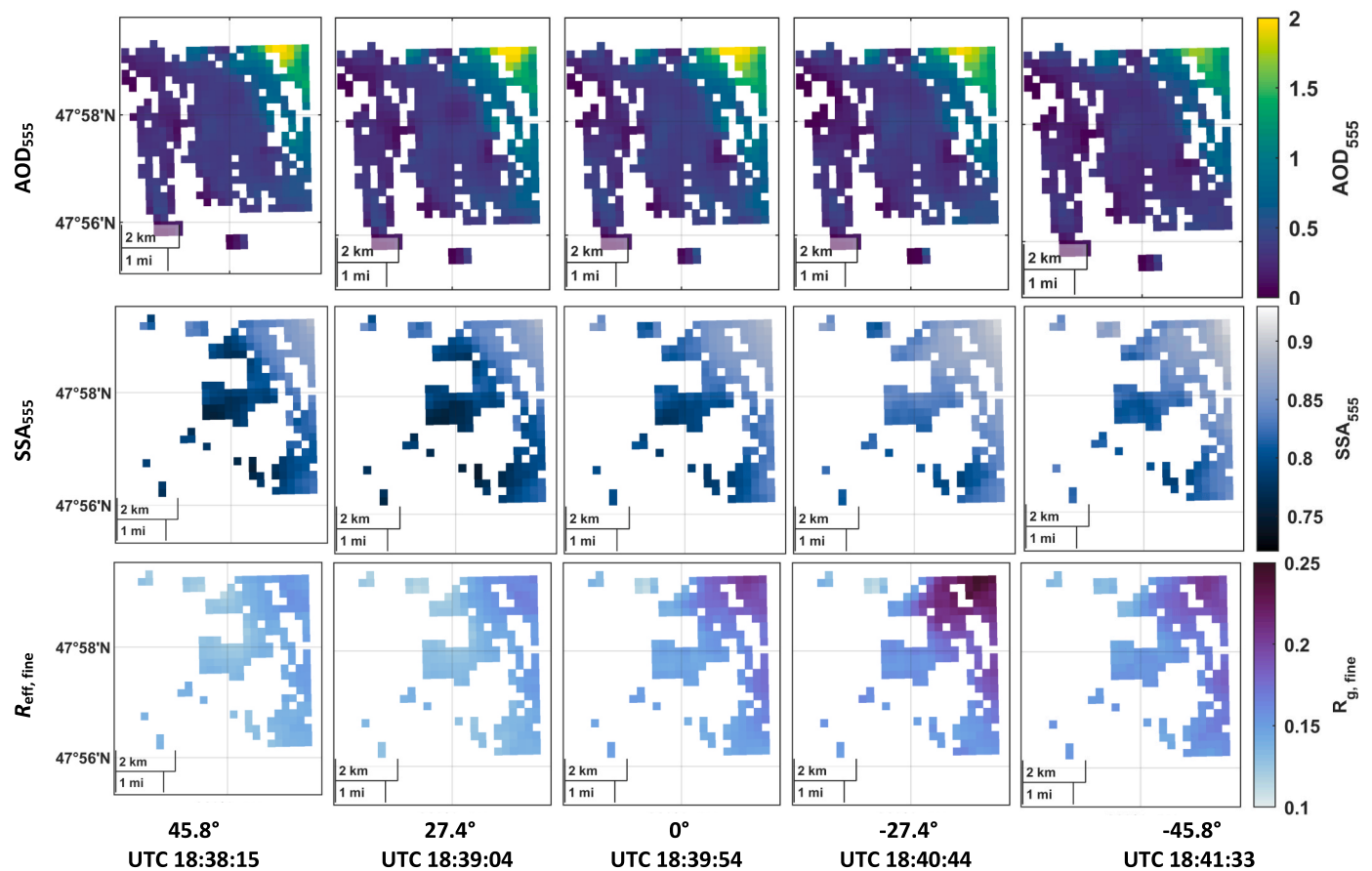


Fig. 18. Single-view-angle retrievals of aerosol properties including AOD_{555} , SSA_{555} , and effective radius of fine mode aerosols ($R_{eff, fine}$) during AirMSPI's ~4-min temporal window covered by five-angle imaging of city Keller. The nadir image was acquired at the UTC time 18:39 on August 6, 2019.

then applied to the data acquired by AirMSPI during the FIREX-AQ campaign. Retrieval comparisons against the collocated AERONET measurements show an AOD difference of less than ~ 0.05 under clear-sky conditions. For smoke plumes with moderately low to high AOD, our retrievals were spatially consistent with eMAS products.

Our test also indicates improved retrieval accuracy when AirMSPI's four most oblique viewing angles (i.e., $\pm 65^\circ$ and $\pm 57^\circ$) are excluded from retrieving smoke particles in a wildfire plume. This strategy strikes an effective balance by mitigating the RT modeling error induced by the plane-parallel atmosphere assumption while retaining reasonable information content by retaining an optimized number of viewing angles. Sensitivity tests show that as long as the scattering angular range is preserved and nadir observations are included, retrieval improvement can be obtained from using three to five viewing angles to retrieve light to moderately dense smoke plumes. For dense smoke, reducing the number of viewing angles from five reduces retrieval stability and is therefore not recommended. We also demonstrate that single-view-angle retrievals can be improved when they are initialized with results from multi-view-angle inversion. The developed algorithm and the findings of this study are expected to assist the retrieval of future multi-angle polarimetric measurements, such as those from the INjected Smoke and PYRocumulonimbus Experiment (Peterson et al., 2024).

Despite these advances, several limitations and unresolved challenges remain for plume remote sensing. First, wildfire smoke plumes often exhibit strong three-dimensional structures and pronounced horizontal heterogeneity. When multi-angle observations are interpreted using a plane-parallel atmospheric representation, modeling errors may arise, particularly for large off-nadir viewing angles. Second, different AirMSPI viewing angles may sample slightly different portions of an evolving plume, which can introduce inconsistencies when these

observations are interpreted as representing a single atmospheric column. Third, differences in spatial resolution between AirMSPI retrievals (~ 250 m) and reference datasets such as eMAS (~ 500 m) may introduce discrepancies in regions with strong spatial gradients in aerosol optical depth. Finally, while AOD retrievals can be compared with AERONET and eMAS measurements, independent validation data for aerosol microphysical properties are generally unavailable for these plume cases, limiting the ability to perform a fully quantitative assessment of retrieval accuracy. In the absence of independent, spatio-temporally collocated reference measurements for validating our retrieved aerosol microphysical properties, the analyses conducted here are therefore qualitative and focus on the physical plausibility of the spatial variations in the retrieved quantities. Ongoing and future efforts focus on two aspects. In the short term, we are quantifying the impact of plane-parallel RT modeling errors on smoke retrieval via a truth-in-truth-out test, namely using synthetic data generated from a 3-D RT model to simulate AirMSPI observations and then test their retrieval using the plane-parallel RT model. In the long term, we will explore the direct use of a 3-D RT model and combined passive-active measurements to enhance plume retrieval, which could reduce modeling errors and enable all nine AirMSPI viewing angles to be exploited to further constrain smoke particle properties.

CRediT authorship contribution statement

Benting Chen: Conceptualization, Data curation, Formal analysis, Investigation, Visualization, Writing – original draft, Writing – review & editing. **Congcong Qiao:** Writing – review & editing. **Feng Xu:** Conceptualization, Funding acquisition, Methodology, Supervision, Writing – review & editing. **Olga V. Kalashnikova:** Writing – review & editing.

editing. Yingxi Rona Shi: Writing – review & editing.

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

The AERONET data used for validation in this study are publicly available from the AERONET website (<https://aeronet.gsfc.nasa.gov/>). The AirMSPI L1B data acquired during the FIREX-AQ field campaign are publicly available from the NASA Langley Research Center Atmospheric Science Data Center (ASDC) at https://asdc.larc.nasa.gov/project/AIRMSPI/AirMSPI_FIREX-AQ_Terrain-projected_Georegistered_Radiance_Data_6. The aerosol product generated by the standard DT algorithm on the eMAS sensor during the entire FIREX_AQ campaign is publicly available via the NASA LAADS website (https://ladsweb.modaps.eosdis.nasa.gov/archive/MAS_eMAS/FIREXAQ/) and the FIREX_AQ data archive (<https://www-air.larc.nasa.gov/cgi-bin/ArcView/firexaq?ER2=1#LEVY.ROBERT/>). Additionally, the final aerosol retrieval data products generated and analyzed in this current study are available from the corresponding author upon request.

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