Response to RC1: egusphere-2025-5824

This study demonstrates the application of two methods for integrating MODIS and MISR satellite data with ground-based observation. The content of the study may be solid, but it is not well-organized and the meaning is not sufficiently emphasized. Before proceeding to the next step, this study/manuscript requires at least an essential revision.

Response: We thank the reviewer for the insightful and constructive comments. We are providing point-by-point responses to each of reviewer's queries below. The relevant texts have also been incorporated into the revised manuscript.

General Comments:

Query-1: In the abstract section, it seems that the study employed two methods, namely the UK and RK-ML. These two methods have both been suggested to be effective for fusing AOD data in the Indian region in this study. However, the relationship between these two methods is not clear. They seem to be completely separate from each other. Furthermore, do these two methods have distinct advantages in addressing the AOD fusion issue? What are the main contributions of this study? Is the proposed method an existing one or has it been specially modified/adjusted for the India region? These contents should also be reflected in the abstract section.

Response: We sincerely thank the reviewer for the valuable suggestions. We have incorporated all the suggested points in the abstract and the elaborated the same in the revised manuscript, highlighting the following details:

Relationship between UK and RK-ML:

The two methods, Universal Kriging (UK) and Residual Kriging with Machine Learning (RK-ML), are conceptually related but methodologically different. Both approaches utilize the variogram to characterize spatial covariance in AOD data. However, they differ in how the large-scale structure of AOD is modelled. In UK, a trend function represents the deterministic relationship between the response variable (ground-based AOD) and explanatory variables (e.g., satellite AOD). The Kriging procedure then estimates AODs using spatially correlation from variogram. In contrast, Support Vector Regression (SVR) is used in the RK-ML approach to generate an initial prediction of AOD, which serves as a prior estimate. The residuals (difference between observed ground AOD and SVR-predicted AOD) are subsequently interpolated using Ordinary Kriging (OK) with spatial covariance derived from the variogram and summed up with the SVR predicted AOD. Thus OK, unlike UK, does not employ an explicit trend function; instead relies solely on spatial correlations among nearby observations. Thus, both methods share the same geostatistical foundation (variogram-based spatial modeling) but differ in how the mean structure of AOD is estimated.

Distinct advantages of the two methods:

The two methods (UK and RK-ML) have different advantages for addressing the AOD fusion problem. UK is effective when the relationship between satellite AOD and ground AOD is adequate to represent by a trend model, and when ground observations are relatively well distributed spatially. On the other hand, RK-ML is advantageous when ground AOD measurements are sparse or unevenly distributed, which is common across large regions of India. In this approach, the machine-learning model (SVR) captures the large-scale variation of AOD, while kriging is applied only to the residuals. Given robust predictions from the ML model, the residuals generally exhibit a near-zero mean at locations far from observations, interpolating them helps avoid distortion of AOD values.

Main contributions of this study:

The main contributions of this study primarily focuses on the evaluation and comparison of two geostatistical–machine learning fusion frameworks (UK and RK-ML) for integrating satellite and ground-based AOD observations over India. It has been demonstrated that RK-ML improves AOD estimation under sparse ground observation conditions, which is a common limitation in the Indian monitoring network. Thus, developing of a robust AOD fusion framework that combines satellite data, ground observations, machine learning prediction, and spatial interpolation to generate improved spatial AOD fields is a novel contribution from this study.

Novelty of the fusion framework (present study):

The RK-ML framework is a novel idea to combine the different datasets for fusion process. However, it is based on established concepts in residual Kriging and machine learning regression. In this study it is specifically implemented and evaluated for AOD data fusion over the Indian region, considering the unique challenges of sparse and unevenly distributed ground AOD observations. The methodological adaptation lies in integrating SVR-based AOD prediction with residual kriging to better handle data sparsity across the Indian domain.

All the above points are now included in the abstract. The revised version of the abstract is included below: We have included the above pointes in the abstract of the revised manuscript (**lines: 11-32**) to better reflect the understanding of the two approaches.

Abstract (revised): "Synergistic fusion of aerosol parameters from multi-sensor measurements is crucial for integrating diverse data sources and generating consistent representations of aerosol distribution for accurate climate impact assessment. In this study, satellite observations from MODIS (Moderate Resolution Imaging Spectroradiometer) and MISR (Multi-angle Imaging SpectroRadiometer) are combined with ground-based measurements from Multi-Wavelength solar Radiometers (MWR) and CIMEL sun-photometers from the ARFINET and AERONET respectively to generate fused Aerosol Optical Depth (AOD) fields over India. The primary focus of this study is to develop a fusion framework over India, involving the evaluation and comparison of two approaches Universal Kriging (UK) and novel hybrid geostatistical-machine learning approach (RK-ML). Both methods share the same geostatistical foundation (variogram-based spatial-modelling) but differ in how the mean structure of AOD is estimated. In UK, satellite-derived AOD serves as deterministic trend for spatial prediction and is effective when ground based observations are well distributed, whereas RK-ML considers SVR-predicted AOD as prior and applies Ordinary Kriging to interpolate residuals from real-time ground observations, maintaining a near-zero residual mean away from observations which reduces distortion under sparse and uneven data conditions. Our results highlight seasonal fused AOD maps (winter, pre-monsoon, and post-monsoon) over India. Leave-One-Out Cross-Validation (LOOCV) is adopted as an evaluation strategy for assessing model performance, showing that the 95% confidence interval ($\pm 2\sigma$) of the fused AOD captures over 80% of ground observations, indicating effectiveness in capturing regional aerosol variability. RK-ML demonstrates more stable spatial patterns and improved LOOCV performance compared to UK, particularly in regions with limited ground-based coverage."

Query 2: The introduction section also should be revised and improved, mainly in two aspects:

(1) Some of the current advanced research findings have not been mentioned or introduced. For example, regarding synergistic inversion (10.1029/2024GL113448; 10.5194/amt-18-7679-2025), data filling (10.5194/essd-16-2425-2024; 10.5194/amt-17-4317-2024), and some physical-based ML method (10.1016/j.rse.2023.113763). These three aspects, although not the main focus of the study, are still closely related to the topic.

(2) In the second paragraph of the introduction, the author lists a large number of methods (Line 67-81). But these methods were basically not discussed at all. Although I do not object to the author's highlighting the advantages of the Kriging method, a brief description of the advantages, disadvantages and applicable scope of various methods should also be provided. Otherwise, the advancement/necessity of the research methods will be difficult to be shown.

Response: Complied with thanks. We have updated the introduction incorporating the citations from current advanced findings, as suggested by the reviewer. We have also revised the introduction providing a brief description of the advantages, disadvantages and applicable scope of various data fusion methods and highlighted the importance of the fusion framework adapted in the present study.

Line 64-69: "In this context, there is a considerable effort in improving aerosol retrieval accuracy using approaches such as synergy processing of sun-photometer and lidar observations (Jin et al., 2025), synergistic retrieval from multi-mission space-borne measurements (Litvinov et al., 2025), gap-filling based on improved tensor-flow-based method (Bai et al., 2024), and the application of physics-informed deep-learning framework to multi-angle polarimetric measurements (Tao et al., 2023)."

Line 76-100: "Several approaches have previously been developed for multi-sensor data fusion involving satellite-to-satellite and satellite-to-ground observations. One notable method is the use of point spread function (PSF) modeling for single scanning footprints (Gupta et al., 2008). While PSF-based techniques are widely applied in image fusion, they face challenges in achieving accurate spatiotemporal colocation across different satellite platforms and don't show applicability regarding ground based AOD fusion rather solely on satellite footprint as a weighting factor for the merging of AOD from different sensors, such as MODIS (Moderate Resolution Imaging Spectroradiometer) and MISR (Multi-angle Imaging SpectroRadiometer) and Clouds and the Earth's Radiant Energy System (CERES). Statistical approaches such as Maximum Likelihood Estimation (Kim et al., 2024; Nirala, 2008) and Bayesian Maximum Entropy (Tang et al., 2016) have been applied to integrate satellite and ground-based observations. These methods explicitly account for uncertainty; but, their practical implementation is often limited by high computational demands, as they require large datasets for effective sampling and detailed pixel-level uncertainty characterization to produce reliable fused products. Similarly, approaches such as the Ensemble Kalman Filter (Li et al., 2020) improve uncertainty quantification and have been applied at the global scale; however, their application is constrained by substantial computational cost and data requirements. These limitations pose challenges for near-real-time applications and for achieving high regional accuracy, particularly in regions with limited ground-based observational support. Simpler least-squares-based approaches, including adaptive weighted estimation (Guo et al., 2013) and semi-empirical optical algorithms (Xu et al., 2012), offer computational efficiency; however, their validation and broader applicability remain uncertain. More recently, machine learning techniques, particularly deep neural networks (DNN) (Kim et al., 2024), have demonstrated comparable performance, but their dependence on large training datasets and challenges in generalization limit their practical deployment."

Line 106-116: "Notably, though geostatistical approaches provide a promising framework for data fusion, they are constrained by high computational demands, particularly when incorporating both spatio-temporal autocorrelation and covariance matrix inversion. Hence, reduced-rank methods such as Spatial statistical data fusion (SSDF) (Puttaswamy et al., 2014; Nguyen et al., 2012) alleviate computational burden but may introduce overfitting due to more number of parameters. Under such a scenario, Universal Kriging (UK) offers more stable AOD estimates near domain boundaries owing to its simpler and more robust formulation (Puttaswamy et al., 2014). Consequently, UK has been widely adopted for multi-sensor fusion integrating satellite and ground-based observations (Chatterjee et al., 2010; Jinnagara Puttaswamy et al., 2014; Lilla and Castrignanò, 2019), although it does not explicitly account for sensor-specific uncertainties."

Line 161-165: In this study, we primarily implement the UK framework over the Indian region to generate monthly fused AOD. Additionally, we evaluate and compare both the geostatistical-machine learning fusion frameworks (UK and RK-ML) while integrating satellite and ground-based AOD observations over India. We further assess the sensitivity of the fusion to the density of ground-based observations, demonstrating how sparse networks can introduce artifacts.

Query 3: I noticed that the grid used in this study is 0.5°, which is commonly employed in some atmospheric models. But for a regional study, this resolution might be rather coarse, especially since the satellite data used has a higher spatial resolution (~ 10 km and 4.4 km). Is this step of reducing the resolution necessary? What studies does the merged data in this study serve for?

Response: We thank the reviewer for pointing out this important aspect. We acknowledge that satellite products such as MODIS (~10 km) and MISR (~4.4 km) provide higher spatial resolution, which can potentially capture finer regional variability in aerosol distributions. Although satellite products provide finer spatial resolution, direct comparison with ground-based point measurements introduces representativeness errors due to scale mismatch. Aggregating the data to a coarser grid (0.5°) reduces this mismatch by ensuring that both satellite and ground observations represent comparable spatial scales, thereby improving the robustness of validation and fusion. The choice of 0.5° represents a balance between retaining regional variability and ensuring sufficient data density within each grid cell for stable statistical estimation and fusion. Thus, this approach ensures consistency between datasets and facilitates reliable comparison and validation with ground-based observations based on a spatio-temporal collocation strategy.

The above points are included in the revised manuscript.

Line 288-316: "As a first step of the fusion processes, the correlation analysis between the satellite and ground-based AOD was made to understand the association/ biases between the two data sets at different spatiotemporal scales. This is useful to understand the requirement of multi-sensor data fusion. For this, a statistical spatio-temporal matching approach (similar to those reported elsewhere by Basart et al., 2009; Chu et al., 2002; Filonchyk et al., 2019; Ichoku et al., 2002) was applied, in which satellite observations were spatially averaged at 0.5° spatial resolution and compared with ground-based AOD averaged within a 30 minute time window around the overpass time of the TERRA satellite which accommodated 14 to 15 measurements from MWR (data frequency 2 min) and 1 to 2 measurements from CIMEL (data frequency 15 min) observations. Although satellite products such as MODIS (~10 km) and MISR (~4.4 km) provide higher spatial resolution potentially capturing finer regional variability in aerosol distributions, yet their direct comparison with ground-based point measurements introduces representativeness errors due to scale mismatch. Aggregating the data to a coarser grid (0.5°) reduces this mismatch by ensuring that both satellite and ground observations represent comparable spatial scales, thereby improving the robustness of validation and fusion. Thus, the choice of 0.5° represents an optimal choice, yielding higher correlation and lower root mean square error (RMSE) (Figs. S2a, b), in addition to retaining regional variability and ensuring sufficient data density within each grid cell for stable statistical estimation and fusion. The consideration of 0.5° resolution is in line with approach adopted by Tandule et al., (2026) for retrieving AOD from satellite observations, ensuring improved representativeness and temporal consistency in comparisons between satellite-derived and ground-based AOD. In addition, generating AOD at this resolution provides a valuable reference dataset for comparison and validation against reanalysis products and model outputs of AOD, where satellite observations are commonly assimilated as primary inputs. Further, AOD observations in this study were aggregated to a monthly scale to ensure more consistent spatial coverage and improve the reliability of multi-sensor fusion analysis. Due to the differences in spatial coverage and revisit characteristics of MODIS and MISR as well as temporal gaps in data availability from ground-based instruments (Figs. S3a, 3b, 3c), daily datasets often contained substantial spatial gaps over the study domain."

Query 4: The author has provided a detailed explanation of the calculation process of methods such as Variogram Analysis and UK, which is good. However, there seems a lack of description regarding the application region of these methods. For instance, the author states that the ground AOD is regarded as the response variable, while the satellite AOD is considered as the regressors (Line 302) in the final spatial fusion. Does this above process also apply to the gap filling step? Were the MODIS and MISR data processed for gap filling separately? Were MODIS and MISR data used simultaneously during the fusion process? Have these two sets of data taken into account the differences in their accuracy (or EE%)?

Response: We thank the reviewer for highlighting the need for clarification on fusion process. Reviewer may kindly note that both MODIS and MISR data were processed separately for gap filling. After the gap filling step, both MODIS and MISR data were incorporated together in the final fusion stage to derive the spatially fused AOD field.

For the gap-filling, the spatial trend model is constructed using geographical parameters such as latitude, longitude, and elevation corresponding to MODIS and MISR AOD. For each of the sensors, variograms were obtained and used along with trend model (as mentioned previously, which are obtained based on geographical parameters such as latitude, longitude, elevations) to generate interpolated pixels, thus filling the gap areas.

Concerning the accuracy (or EE%) of MODIS AOD, MODIS Dark Target–Deep Blue combined product at 550 nm were utilized, with approximately 90% of the data shows high-quality retrievals (QA = 2, 3). Similarly, MISR AOD data were incorporated along with their associated uncertainty estimates, with about 88% of the observations exhibiting uncertainties in the range of 0.02–0.08 and an average uncertainty of approximately 0.05. No additional filtering was applied during the fusion process beyond these quality constraints, as further screening may attenuate the inherent systematic bias between satellite-derived and ground-based AOD observations and potentially distort their true association.

The above discussions are included in the revised manuscript.

Line 255-260: In the fusion approach, MODIS AOD represents high-quality retrievals (QA = 2, 3), while MISR exhibits minimal retrieval uncertainties (0.02–0.08) over ground stations. Additional screening or filtering was not applied beyond these criteria, as it may attenuate the inherent systematic bias between ground- and satellite-based observations. Quality-assured and expected-error-based filtering can be considered as part of the future scope of the study to enable more accurate inferences.

Line 430-435: "Our foremost approach involved creating a trend model for fusion. For this purpose, we generated a complete satellite-based map of AOD from MODIS and MISR separately over the study region using the UK method. In this framework, geographical parameters such as latitude, longitude and elevation are treated as regressors (trend model), whereas observed satellite data serve as response variables to fill the gaps in individual satellite datasets."

Query 5: The discrepancy between the ground data and the satellite data is what I am concerned about. MODIS observations (Figure 3) have revealed the familiar AOD distribution pattern in South Asia. However, it seems to have a significant difference from the ARFINET results obtained through ground-based observations. Especially in the high-value areas in the north, these data seem to have been completely unobserved from ARFINET. Without considering the issue of the instrument itself, this phenomenon might be caused by the algorithm mistakenly classifying haze (high aerosol loading) as clouds (10.1109/TGRS.2023.3252264) and this caused all the high values to be blocked. However, in any case, if there is a significant discrepancy or difference between the ground data and the satellite data in the overall trend distribution, this will have an impact that cannot be ignored on the subsequent results.

Response: We appreciate the reviewer's comment on this matter. To examine this issue, we analysed both ground-based and MODIS AOD at each of the station locations, particularly over northern India and the inter-comparison results are presented in the revised manuscript. We have also highlighted the discrepancies between the satellite and ground based AOD and possible reasons for such discrepancies (including the haze removal) are discussed. The following details are now included in the revised manuscript.

Line 563-586: "Though dominant spatial patterns are same in long term AOD from spaceborne sensors and their differences with ground-based AOD over same spatial grids are minimal (**Figs.**

S7a, b), the discrepancy persists, especially over northern India and during monsoon period. As cloud-haze misclassifications may act as one of the factors from the observed differences between satellite and ground AOD in the monsoon periods, haze-removal criteria (following Jiao et al., 2023) to MODIS AOD was applied. A significant impact of haze over the peninsular region is seen during monsoon (**Supplementary Figs. S7c, d**), however, it shows negligible influence during the other seasons. This is clearly seen from the difference maps between the MODIS and ground-AOD over different ground locations, showing minimal changes before and after the haze removal. This exercise suggests that cloud–haze misclassification is not the primary factor driving the observed differences, except under monsoon conditions. Under such a scenario, localized discrepancies may arise due to spatial sampling limitations of the ground-based observations. As the ARFINET stations are sparsely and unevenly distributed, particularly across regions of high aerosol loading in northern India, this may result in the apparent lack of complete regional representation of ground observations. Additionally, discrepancies between MODIS and MISR AOD are also seen owing to fixed and multi angle retrievals especially in Pre-monsoon period over the NW region, where MISR AOD is significantly different from MODIS. There are also some pockets where low AOD region observed by MODIS is alternatively represented as a region of higher AOD in MISR observations, particularly in proximity to the IGP outflow. Previous studies over similar geographic regions have indicated that the frequency of observations, cloud masking, and geographical factors impact both MODIS and MISR observations, stemming from algorithm assumptions related to cloud masking and SSA."

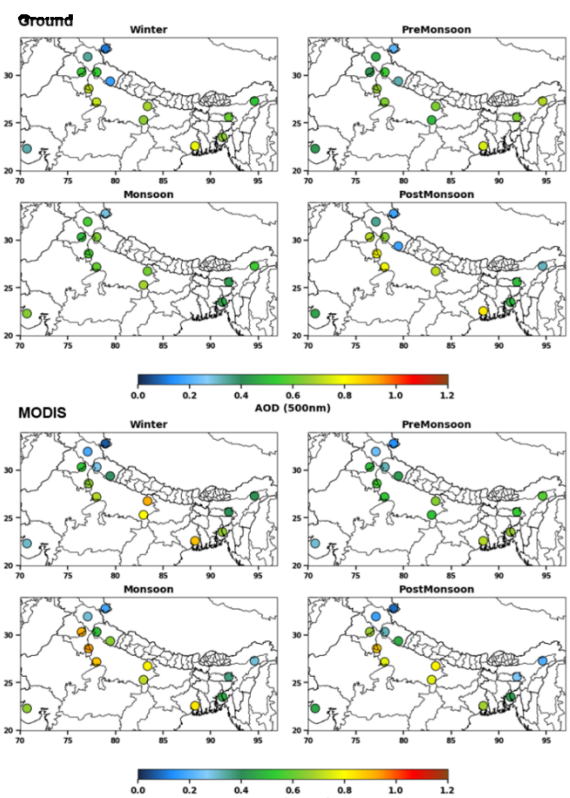

Figure-S7a: Comparison of seasonal average AOD from ground-based and satellite (MODIS) observations over different ground locations of ARFINET.

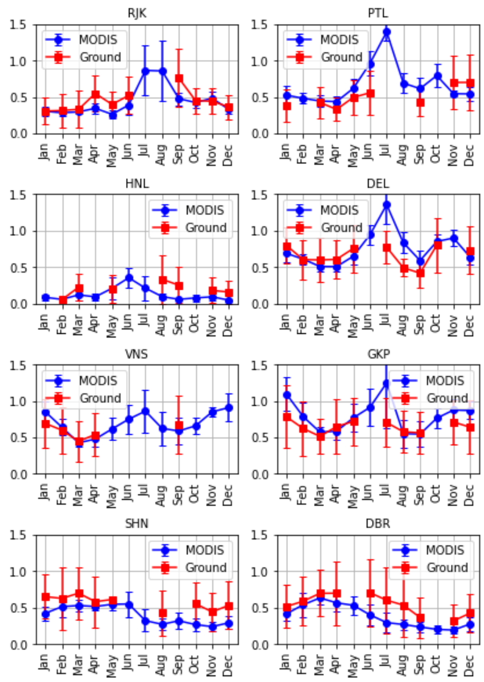

Figure-S7 b: Time series plots of long-term MODIS and ground-based AOD (monthly mean) over selected locations of ARFINET.

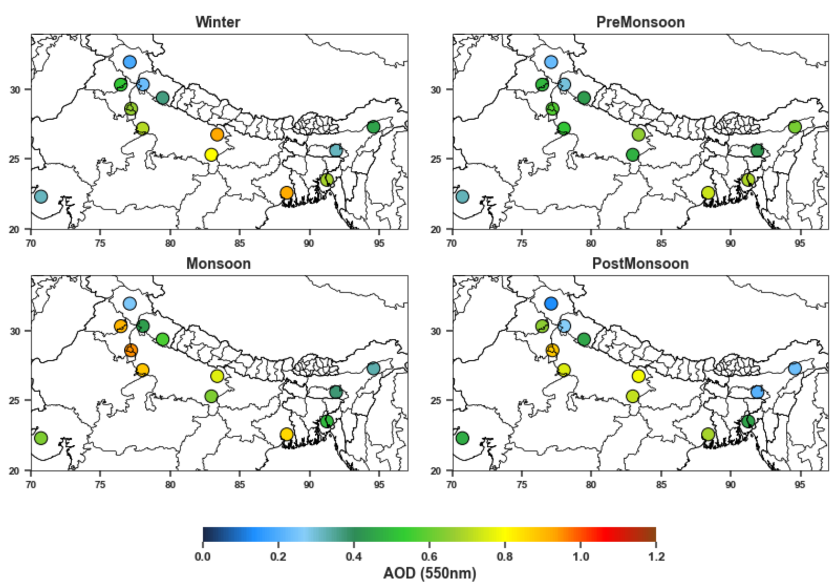

Figure-S7 c: Long-term seasonal mean AOD over ground monitoring locations derived from MODIS AOD after applying haze-removal criteria.

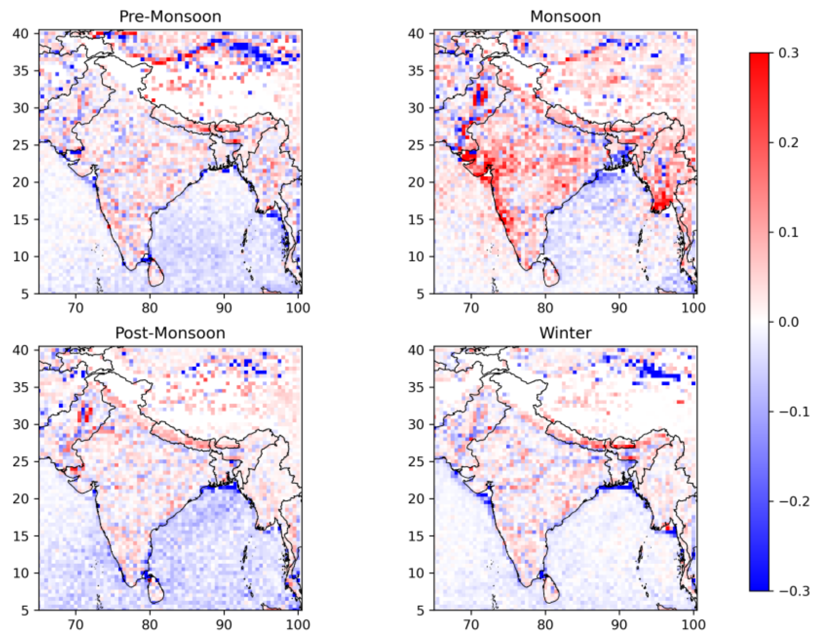

Figure-S7 d: Difference between long-term seasonal mean AOD derived from MODIS AOD before and after applying haze-removal criteria.

Line 601-608: "Despite the above constraints, the general agreement in magnitude and temporal variability supports the reliability of both datasets for the fusion framework. Thus, our approach explicitly accounts for such discrepancies by integrating the broad spatial coverage of satellite observations with the higher accuracy of ground-based measurements. In this context, ground observations are treated as local constraints rather than complete spatial representations, thereby minimizing the influence of regional sampling gaps in the ground network. Consequently, the final fused AOD represents a bias-corrected satellite-derived field constrained by ground observations."

Query 6: Is there a way to simply evaluate the interpolated results? Otherwise, the information conveyed in 3.3.2 section is rather limited.

Response: We carried out sensitivity studies by removing some of regions manually targeting heterogeneous landmasses and predicted using the remaining datasets. The updated discussion is incorporated in the revised manuscript, as given below:

Line 706-717: "The spatial distribution of 0.5° gridded monthly mean raw and predicted (after spatial interpolation) AOD from MODIS and MISR is shown in supplementary **Figs. S18-S23**. The performance metrics (in terms of R and RMSE) of this gap-filling approach are demonstrated through sensitivity studies, considering different spatial gaps in the data (**Fig. S24**). It is observed that the predicted AOD largely depends on the availability and spatial distribution of nearby observed data points. Regions such as the IGP, the Himalayan region, peninsular India, and oceanic areas generally show better performance, where smoother spatial gradients of AOD and more consistent regional aerosol patterns improve the reliability of the spatial predictions. Based on these sensitivity studies, the predicted AOD field appears to provide a reliable spatial representation with acceptable uncertainty as the interpolation (gap filling) is made over a relatively small fraction of missing values based on a large number of observed data points around the gap areas."

Query 7: Is the fused AOD (Figures 4, 5, 6) calculated using UK method? Please Clarify. Furthermore, I can observe some high-value points/regions in the figure, such as Figure 5k and Figure 6f. Its value is higher than that of MODIS and MISR simultaneously, but there is no supporting data from ground stations. Therefore, it is difficult to explain.

Some recent Publications should be discussed, for example, Significant uncertainties from overlooking aerosol-cloud coexistence in surface solar radiation estimates using passive satellite observations; Effects of Different Types of Aerosols on Diffuse Radiation Based on Global AERONET; First high temporal resolution retrievals of AOD over shallow and turbid coastal waters for Himawari-8; Synergistic Estimation of Surface Particulate Matter and Ozone Pollutants to enhance accuracy and interpretability by a Deep Learning Approach; A Physics-Guided Neural Network Model to Estimate All-Sky Diffuse Solar Radiation Using Himawari-8 Data.

Response: Yes, the fused AOD shown in **Figures 4, 5, and 6** is derived using the UK fusion method, which combines information from multiple satellite products to obtain a spatially consistent AOD field. We have clarified this in the revised manuscript.

Line 719-720: "The monthly fused AOD is generated using the UK fusion method, where satellite data are treated as trend model."

We have also revised the discussion on the certain high-value regions in **Figure 5 and Figure 6,** where the fused AOD exceeds both MODIS and MISR, and supporting ground-based observations are limited. The suggested references are also included in the discussion.

Line: 757-765: "Notably, the discrepancies seen near coastal regions in May (2021), particularly across the peninsular zone, may be attributed to higher cloud fractions (**Fig. S25**), introducing greater uncertainty in aerosol-cloud discrimination (Lang et al., 2026), thereby leading to inaccuracies in satellite-derived AOD estimate. Furthermore, AOD retrievals in coastal areas may also be influenced by potential overestimation of boundary layer height (BLH) in MODIS data (Wang et al., 2025a). The fused AOD, which primarily incorporates the information from the availability and spatial proximity of ground-based measurements, tends to show higher values in these regions, effectively correcting this bias using ground-based observations."

Line: 777-779: "Here, the fused map showed enhanced AOD attributed to observations from ground stations, viz. Chennai (CHN) and Kadapa (KDP), which were underestimated by both MODIS and MISR."

Line: 792-796:"Overall, the fused AOD is constrained locally on ground-based AOD, which are generally considered more accurate than satellite-based observations whereas satellite retrievals exhibit discrepancies due to variations in aerosol types and their source contributions, which likely explain the observed differences in AOD estimates (Li et al., 2025; Wang et al., 2025b)."

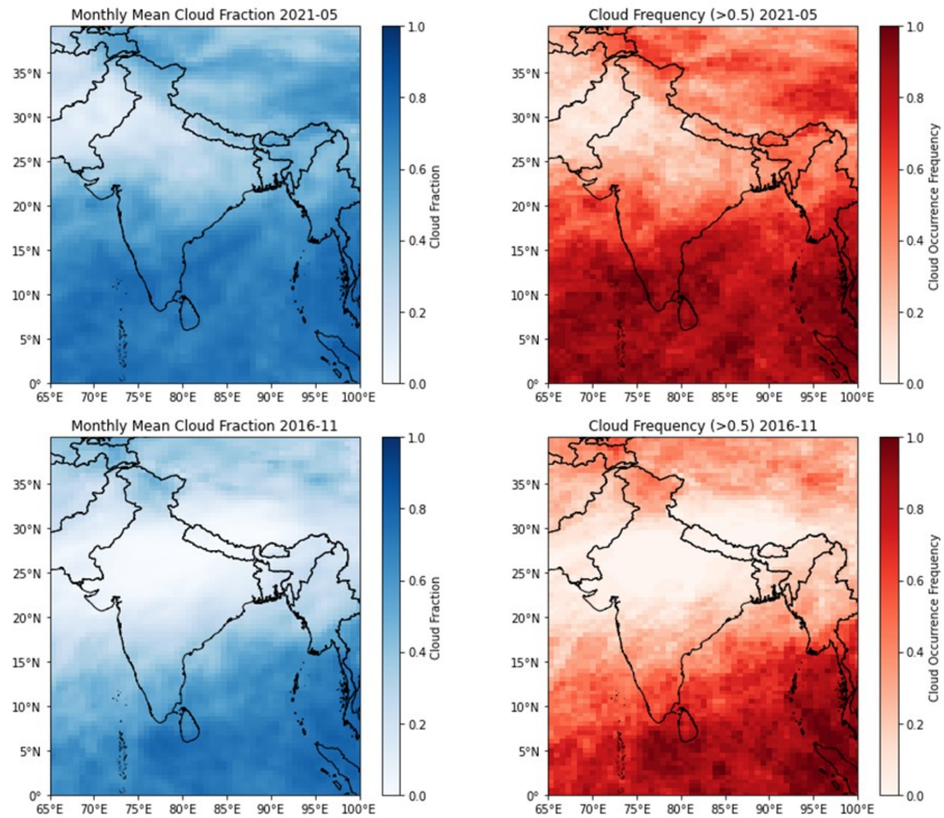

Figure – S25: Monthly mean cloud fractions (Left panels) and cloud fraction frequency per month of occurrence for the cloud fractions >0.5 (Right panels). For the May 2021 (top panels) and November 2016 (bottom panels). Cloud fraction map for Indian region from MERRA2 cloud fraction indicates the number of cloudy pixels during (10:00 AM – 11:00 AM IST) time, cloud frequency shows how many days were cloudy in that month cloud frequency for cloud fraction>0.5.

Query 8: Can we increase the contrast/validation between the fusion results and the ground, as shown in Tables 4 and 5?

Response: Complied with, we have included the contrast/ validation results between fused AOD and ground-based AOD in Table ST7 and the relevant text is updated in the revised manuscript.

Line 727-728: "As shown in **Table 4**, the fused AOD is more aligned to ground-based AOD with a correlation (R) ~0.994-1 and RMSE ~0.009-0.04."

Table - 4: Comparative analysis of fused vs ground AOD at ground station locations.

Year	Month	Fused & Ground				
		Correlation	RMSE	MAE	slope	bias
2012	Jan	0.998	0.014	0.011	1.024	0.003
	May	0.998	0.014	0.011	1.012	0.003
	Nov	0.996	0.025	0.017	1.026	0.004
2016	Jan	0.994	0.032	0.023	1.026	-0.006
	May	0.984	0.04	0.026	1.074	0.004
	Nov	0.994	0.026	0.018	0.994	-0.003
2021	Jan	0.999	0.022	0.015	1.03	0.008
	May	0.998	0.022	0.016	1.049	0.009
	Nov	1	0.009	0.007	1.003	0.002

Query 9: The Limitation section (3.3.6) is not good here. Discussions on minor technical details will increase doubts about your method. Such as many of the contents in this section have not been discussed or elaborated upon in the previous text. If one wants to discuss the limitations of the research, it should be explained from the perspective of scientific methodology.

Response: We have removed this section and included the relevant discussion in the methodology.

Specific Comments:

Query 10: Line 102: The full name of the ARFINET site should be provided, and a brief introduction to the development history of this network should also be given.

Response: Complied with.

Line 124-130: "In this study, AOD measurements carried out from more than 40 ground-based observatories of the Aerosol Radiative Forcing over India Network (ARFINET; **Fig.-S1a**), which constitutes the national network of aerosol observatories across India and the largest such network in South Asia, are primarily used to integrate with the satellite-based observations from MODIS (Moderate Resolution Imaging Spectrometer) and the MISR (Multi-angle Imaging Spectro-Radiometer) to generate fused AOD using UK framework."

Line 168-170: "The ground-based AOD is primarily obtained from ARFINET observations, having continuous measurements across the Indian region since 1985 maintained under ISRO-GBP (Gogoi et al., 2009; Babu et al., 2013)."

Query 11: Line 106: what is the frequency of data observation?

Response: The data frequency varies among the individual observation platforms within a month. Ground stations and MODIS indicate approximately 41–49% observations within a month, with a gap of about 2–3 days. This corresponds to roughly 10–15 days of data collected across different stations over the month. In contrast, MISR shows around 26% observations with an average gap of about 4 days, which is equivalent to nearly 7 days of data across various stations within the same period. In the revised manuscript, this information is included to demonstrate the representativeness of the monthly observations.

Line: 314-316: "Due to the differences in spatial coverage and revisit characteristics of MODIS and MISR as well as temporal gaps in data availability from ground-based instruments (Figs. S3a, 3b, 3c), daily datasets often contained substantial spatial gaps over the study domain."

Figure S3a. The compiled ground-based dataset consists of 2507 observation days across 22 stations on average per month during January, May, and November for the years 2012, 2016, and 2021. This corresponds to approximately 41% of the maximum possible observations, which is consistent with typical data availability in aerosol observations primarily influenced by cloud screening and instrument downtime. The average temporal sampling gap is ~3–4 days, indicating adequate coverage for reliable monthly statistics.

Figure S3b. MODIS provides approximately 49% of observations (days) in a month.

Figure S3c. MISR observations occur on average 25.6% of the days in a month, corresponding to a mean revisit interval of approximately 4 days.

Query 12: Line 140: When estimating the AOD at 550nm using the wavelength-dependent relationship of AOD, which two wavelength bands were used for the calculation?

Response: "For this study, values of α were estimated from the wavelength dependent relationship of AOD at 450 and 650 nm for MWR, and 440 and 670 nm pair for CIMEL. Using this, AOD at 550 nm was estimated; where the base AOD was taken at 500 nm (in case missing AOD at 500 nm, base AOD at 440 or, 450 nm was considered)."

We have included information in the revised manuscript (**lines: 216-220**).

Query 13: Line 183-186: Specifically, what methods and concepts were introduced?

Response: The sentence was for referring the concepts of spatio-temporal matching described by some of studies. We have reframed the sentence in the revise manuscript for better clarifications.

line-291-300: "For this, a statistical spatio-temporal matching approach similar to those elsewhere by Basart et al., (2009);Chu et al., (2002); Filonchyk et al., (2019); Ichoku et al., (2002) was applied, in which satellite observations were spatially averaged at 0.5° spatial resolution and compared with ground-based AOD averaged within a 30 minute time window around the overpass time of the TERRA satellite which accommodated 14 to 15 measurements from MWR (data frequency 2 min) and 1 to 2 measurements from CIMEL (data frequency 15 min) observations. Although satellite products such as MODIS (~10 km) and MISR (~4.4 km) provide higher spatial resolution potentially capturing finer regional variability in aerosol distributions, yet their direct comparison with ground-based point measurements introduces representativeness errors due to scale mismatch."

Query 14: Section 2.3.4: The first paragraph of this section seems more appropriate to be placed in the introduction section.

Response: Complied with. We have moved relevant portion of this section to introduction.

Line: 135-160: "While satellite and ground-based AOD measurements generally exhibit a linear correlation, regional and environmental factors introduce biases, noise and nonlinear dependencies between explanatory and response variables. Although nonlinear extensions within the UK framework are possible, they require sophisticated techniques to achieve optimal performance, making the hybrid approach a compelling alternative. While the trend component in UK framework is conventionally modeled using low-order polynomials (e.g., first or second degree), studies exploring non-linear trend modeling are still relatively rare. For instance, Snepvangers et al. (2003) incorporated a logarithmic trend to improve prediction of soil water content using net precipitation as an auxiliary variable. Freier and Lieres (2015) proposed a Taylor-based linearization technique combined with iterative parameter estimation to capture non-linear trend functions in UK. Freier et al. (2017) further extended this approach to interpolate low-density, irregular biocatalytic data. These techniques are effective when the functional form of the non-linearity is known a priori. However, in most practical scenarios, such explicit formulations are unavailable due to complex, unknown interactions between design factors and responses. In this context, machine learning (ML) models, especially kernel-based methods such as Support Vector Regression (SVR), offer an effective alternative for capturing nonlinear and implicit relationships from data without the need of predefined functional forms. Considering the usefulness of prior spatial information on AOD across the domain, a hybrid Residual Kriging with Machine Learning (RK-ML) framework is adopted in this study, where SVR is used to generate an initial prediction of AOD, which serves as a prior estimate. The preference for SVR over decision-tree–based algorithms arises from its effectiveness for problems involving a small number of features and limited datasets, enabling more reliable fused estimates even when ground-based observations are sparse. While UK involves weighted regression with spatial covariance structures (for spatial predictions), RK-ML employs ML based regression and spatial covariance structure to produce more efficient and stable spatial patterns."

Query 15: Line 381: What does "LOOCV" mean? Is it for a certain range or a specific site? Furthermore, in some machine learning scenarios, cross-validation based on the site, time, and total sample is also considered to test the overall stability of the model (10.1109/TGRS.2026.3657522).

Query 16: Line 383: Compared with the unbiased estimation model performance, LOOCV is more focused on evaluating the generalization ability of the model, such as in different time and spatial regions.

Query 17: Line 398: Apart from training and testing, are there any uses of individual sample set for validation?

Response: We are sorry for the lack of clarification on the LOOCV. We have revised the text as given below to clearly highlight the message of LOOCV.

In this study, leave-one-out cross-validation (LOOCV) was used during the machine learning model development. In LOOCV, one sample is iteratively used for testing while the remaining samples are used for training, allowing the model to be evaluated across all available observations. Because the sample size in our study was relatively limited, creating independent training, validation, and testing subsets would significantly reduce the number of samples available for model training. Therefore, LOOCV was adopted to make efficient use of the available dataset while assessing the generalization ability of the model.

To clarify this in the manuscript, we have revised the text as follows:

Lines 494–507: "The hyperparameters of the SVR model were optimized using a grid-search strategy as part of the training process. In this approach, predefined values for key hyperparameters - such as the regularization parameter (C), kernel type, gamma (ϒ) and epsilon (ε) - were combined to form all possible parameter configurations, and each configuration was evaluated. For every hyperparameter combination, model performance was assessed using the negative mean squared error (neg-MSE) as the evaluation metric. This metric quantifies prediction error, and allows selection of the best model by maximizing the score. Due to the limited size of the dataset, leave-one-out cross-validation (LOOCV) was used during training instead of k-fold cross-validation. Even though other cross-validation approaches, such as site-based, temporal, or sample-based validation, can also be used to assess model robustness, the LOOCV was considered the most suitable approach in this study considering the limited number of samples and the uneven spatial distribution of ground observations. In LOOCV, the model is trained repeatedly on all samples except one, which is used for validation. This procedure is repeated so that each data point serves once as the validation sample."

Query 18: Line 400-411: This part of analysis is not closely related to the content of this section. It is recommended to remove it or reorganize it into the introduction part.

Response: We thank the reviewer for the suggestion. After revising the introduction, we found that these contents were no longer necessary. Therefore, they have been removed from the revised version of the manuscript.

Query 19: Figure 2: Is there any display of data from AERONET (It was also used in this study)? Furthermore, it would be better to use different symbols to represent different sites.

Response: We thank the reviewer for the suggestion. We have updated our **Figures-4,5,6** in manuscripts where AERONET stations are used as diamond markers while ARFINET stations are circle markers. We have also included the details of all AERONET stations used in this study (**Fig.-S1b**).

Query 20: Line 465: why only using data from 2012, 2016, and 2021?

Response: "The three different years were selected such that way that the AOD for 2012 and 2021 provides the decadal variability, while 2016 represents an intermediate period between these two years, enabling us to better assess the progression and variability of AOD over a long period."

The above information is included in the revised manuscript (**lines: 618-621**).

Query 21: Line 501: Multi-angle measurement makes it easier to describe the anisotropic scattering of the surface (BRDF). However, under high AOD conditions, since the surface reflection is smoothed out by thickness aerosol, it may instead lead to an underestimation of AOD (Then, the contribution of some aerosols in total signal will be wrongly attributed to the surface).

Response: We agree that under high AOD conditions the strong aerosol loading can smooth the surface reflectance signal, which may lead to an underestimation of AOD as part of the aerosol contribution could be misattributed to surface reflectance. We had overlooked this aspect in the earlier version. Following the reviewer's suggestion, we have incorporated this explanation and the related discussion on the limitations of multi-angle measurements under high aerosol loading into the revised manuscript.

Line: 639-644: "MISR tends to underestimate high AOD conditions in urban regions compared to MODIS, even though it can effectively separate surface contributions under low aerosol loading, as also reported by Tao et al. (2020). Under high AOD conditions, the benefit of multi-angle measurements becomes limited, as thick aerosol layers smooth out surface reflectance signals (BRDF), potentially leading to an underestimation of AOD due to misattribution of aerosol contributions to surface reflectance."

Query 22: Figure10: Please clarify the color indications in the column chart.

Response: We have updated the color indications in column chart of **Figure 10**.

Query 23: It is clear that RK-ML is better than UK, rather than being similar to UK and RK-ML as indicated in the Abstract.

Response: We agree that the original Abstract did not clearly reflect the improved performance of RK-ML compared with the UK method. Accordingly, we have revised the Abstract to better clarify this point.

Line: 31-32: "RK-ML demonstrates more stable spatial patterns and improved LOOCV performance compared to UK, particularly in regions with limited ground-based coverage."

-END

Response to RC2: egusphere-2025-5824

Authors employ two-stage Universal Kriging (UK) method for the synergistic fusion of aerosol optical depth dataset from MODIS and MISR, and ground-based ARFINET data over the Indian subcontinent. The seasonal fused maps of AOD integrates more than 80% of the ground-based observations, highlighting the impacts of number of ground measurements in the fusion process. Integrating Machine Learning (ML) approach with the Residual Kriging is found to capturing stable spatial patterns under limited or sparse coverage of ground observations. The paper feels lengthy, but informative and presented with sufficient details (i.e., text, maps, and plots).

We sincerely appreciate the insightful and constructive comments of the reviewer. We have carefully addressed all the queries providing point by point responses to each of them. For clarity, the reviewer's comments are shown in bold green text, and our responses are provided in blue text. The relevant texts have also been incorporated into the revised manuscript.

General Comments:

Query-1: One primary concern with this paper is that the fusion approach has been applied to the monthly mean MODIS/MISR aerosol products, which are already providing spatially extensive distribution of AOD in the first place. The improvements demonstrated by authors add AOD data over very northern parts of India, around Kashmir region, where AOD is very low.

Response: We thank the reviewer for highlighting this important point. We have utilized monthly data sets in the fusion framework, which is designed to operate under practical observational constraints, such as differences in sensor characteristics (e.g., spatial coverage, revisit frequency, and collocation with ground observations), which limit consistent data availability at daily timescales. Hence, the analysis is conducted at the monthly scale to improve spatial representativeness, reduce sampling gaps, and enhance statistical robustness.

Details are included in the revised manuscript.

Line 262-281: "The geostatistical data fusion method used in this study combines spatial data from multiple sources (satellite and ground-based, as detailed in Sections 2.1 and 2.2) with varying resolutions, accuracies, and types of measurements. The aim is to enhance the overall understanding and prediction of spatial variables (e.g., AOD) to produce a more accurate and comprehensive representation of columnar AOD, with an emphasis on reducing inter-sensor biases through integration with ground-based observations. For this, we have adapted UK framework, where data interpolation relies on unknown functions (e.g., satellite derived AOD) represented as trend models with spatial autocorrelation through variogram analysis. Building on this framework, the fusion methodology is designed to operate under practical observational constraints, such as differences in sensor characteristics (e.g., spatial coverage, revisit frequency, and collocation with ground observations), which limit consistent data availability at daily timescales. Hence, the analysis is conducted at the monthly scale to improve spatial representativeness, reduce sampling gaps, and enhance statistical robustness. Notably, the monthly satellite AOD products also retain sensor-specific biases and inter-product inconsistencies. Thus, the fusion approach presented here is not primarily aimed at gap-filling, but at generating a more accurate and internally consistent AOD dataset by integrating complementary information from multiple sensors and ground-based observations. Thus, even at the monthly scale, the proposed method adds value by reducing retrieval uncertainties and improving the reliability of aerosol distributions, which is critical for climate studies and radiative forcing assessments."

Query-2: Another concern is about the choice of satellite sensors. MISR's repeat overpass occurs every 4 days, limiting the spatial coverage and its ability to capture daily changes in aerosol loading. MODIS flies on Terra (morning overpass) and Aqua (early afternoon overpass). The Dark Target and Deep Blue combined AOD product used in the present work is available from both satellites. Utilizing these two MODIS sensors in the fusion process would have offered more complete spatial coverage on daily basis, in addition to the diurnal variations in aerosol patterns.

Response: We thank the reviewer for this important and valuable suggestion.

We agree that incorporating both Terra and Aqua MODIS observations could improve daily spatial coverage and provide insights into diurnal variability. However, the present study is focused on developing a robust multi-sensor fusion framework by combining datasets with consistent overpass times and viewing geometries. Although MODIS AOD provides very good spatial coverage, its retrievals exhibit higher uncertainty over the heavy aerosol loading and high surface reflectance areas (Tian et al., 2018, 2019,Farhat et al., 2019). In contrast, MISR AOD demonstrates greater accuracy over terrains and highly reflective land cover regions due to its multi-angle observation capability (Garay et al., 2017); however, it has a lower temporal resolution with a revisit time of four days. Details regarding the utilization of MODIS and MISR data are included in the revised manuscript.

Line 248-255: "The MODIS and MISR datasets used in this study are both acquired from the Terra satellite platform and therefore have nearly identical overpass times. This temporal consistency ensures improved compatibility in the fusion process and minimizes uncertainties associated with diurnal variability in aerosol loading. In contrast, inclusion of MODIS observations from the Aqua satellite, which has a different overpass time, would introduce additional variability related to diurnal aerosol evolution that requires explicit treatment. Addressing such effects is beyond the scope of the present methodology-focused study and will be considered in future work."

Line 312-316: "AOD observations in this study were aggregated to a monthly scale to ensure more consistent spatial coverage and improve the reliability of multi-sensor fusion analysis. Due to the differences in spatial coverage and revisit characteristics of MODIS and MISR as well as temporal gaps in data availability from ground-based instruments (**Figs. S3a, 3b, 3c**), daily datasets often contained substantial spatial gaps over the study domain."

Line 645-649: "when dust loading is dominated by coarse and non-spherical particles (in May), MISR demonstrates relatively better performance than MODIS (as shown by scatter plots). This difference may be attributed to the advantage of MISR's multi-angle observation capability, consistent with findings from Middle Eastern validation studies (Farahat, 2019; Garay et al., 2017)."

Query-3: Additionally, an application of the UK-ML approach on daily AOD fields would have added more value than the presented monthly scale, at which the satellite aerosol products fill the gaps and provide more extensive spatial coverage.

Response: We fully agree with the reviewer's suggestion that applying the UK/RK-ML approach to daily AOD fields could provide additional insights into short-term aerosol variability. However, such an analysis would require denser and more consistent observational coverage than currently available. In this context, as discussed in our responses to Query-1 and Query-2, the use of monthly averaged AOD products was motivated by the need to ensure sufficient spatial coverage and reliable collocation between satellite (MODIS and MISR) and ground-based (ARFINET/AERONET) observations. At daily timescales, the differences in sensor characteristics—such as MISR's limited repeat cycle and spatial coverage, as well as inconsistencies in collocation with ground observations—result in sparse and uneven data availability over large regions.

We have included the above message in the revised manuscript.

line 262-281: "The geostatistical data fusion method used in this study combines spatial data from multiple sources (satellite and ground-based, as detailed in Sections 2.1 and 2.2) with varying resolutions, accuracies, and types of measurements. The aim is to enhance the overall understanding and prediction of spatial variables (e.g., AOD) to produce a more accurate and comprehensive representation of columnar AOD, with an emphasis on reducing inter-sensor biases through integration with ground-based observations. For this, we have adapted UK framework, where data interpolation relies on unknown functions (e.g., satellite derived AOD) represented as trend models with spatial autocorrelation through variogram analysis. Building on this framework, the fusion methodology is designed to operate under practical observational constraints, such as differences in sensor characteristics (e.g., spatial coverage, revisit frequency, and collocation with ground observations), which limit consistent data availability at daily timescales. Hence, the analysis is conducted at the monthly scale to improve spatial representativeness, reduce sampling gaps, and enhance statistical robustness. Notably, the monthly satellite AOD products also retain sensor-specific biases and inter-product inconsistencies. Thus, the fusion approach presented here is not primarily aimed at gap-filling, but at generating a more accurate and internally consistent AOD dataset by integrating complementary information from multiple sensors and ground-based observations. Thus, even at the monthly scale, the proposed method adds value by reducing retrieval uncertainties and improving the reliability of aerosol distributions, which is critical for climate studies and radiative forcing assessments."

Specific Comments:

Query-4: Abstract: Satellite and ground-based datasets should be introduced first in the abstract, followed by Universal Kriging and ML approaches. (a) The abstract doesn't give an impression of how UK-ML approaches improve spatial distribution of AOD. (b) Have authors validated the fused AOD dataset? Although, ground-based ARFINET data is used in the fusion, the AOD still can be validated against available AERONET sites in India. (c) Also, it is unclear how the suggested fusion approach optimally uses either MODIS, MISR, and ARFINET AOD datasets. Abstract should address these concerns.

Response: Complied with thanks. The abstract is revised introducing the satellite (MODIS, MISR) and ground-based (ARFINET/AERONET) datasets, followed by a clearer description of the UK/ RKML methodology and its advantages. We have included validation details of fused AOD with both ARFINET and AERONET ground based observations.

The abstract clearly highlights the key advancement—namely, the improved spatial stability and reliability of AOD distributions achieved through the RK-ML approach compared to UK, the methodological details are included in the revised manuscript:

Advantages RK-ML:

The primary objective of this study is the fusion of AOD datasets to improve both the magnitude and spatial reliability of AOD across different regions. Our analysis shows that the UK method exhibits limitations under sparse ground-based observations, often resulting in less stable and spatially inconsistent patterns. In contrast, the RKML approach produces a more robust and consistent spatial distribution.

This improvement arises from the methodological framework: UK relies on a deterministic trend model and is therefore sensitive to the distribution of observations. In RKML, a machine learning model (SVR) first captures the nonlinear relationship between satellite and ground-based AOD, and Ordinary Kriging is then applied to the residuals. Because the residuals are small and have near-zero mean, the Kriging step introduces minimal corrections, particularly in regions far from observations. As a result, RKML preserves a stable and realistic AOD distribution, even under sparse observational conditions.

Validation of fused AOD:

The fused AOD dataset has been validated using a leave-one-out cross-validation (LOOCV) approach. This method was chosen considering the limited number of ground-based stations and their uneven spatial distribution across India. LOOCV allows each station to be independently evaluated while maximizing the use of available observations, making it more suitable than K-fold cross-validation or region-based holdout strategies under sparse and heterogeneous sampling conditions.

During LOOCV, we have utilized both ARFINET and AERONET data from ground-based observations. However, it may be noted that during the study period, the number of available AERONET stations within Indian region was limited, and the temporal coverage was not consistent for the selected months.

Fusion approach:

In the proposed fusion framework, satellite-derived AOD products (MODIS and MISR) are incorporated as explanatory variables (or trend components), while ground-based observations (ARFINET/AERONET AOD) are treated as the reference (response variable). Conceptually, this is analogous to a regression-based approach in which satellite datasets provide spatially continuous information, and ground observations are used to constrain and correct the estimates. The fusion method combines these datasets by leveraging both the large-scale spatial patterns captured by MODIS and MISR. In this framework, ground-based observations play a critical role in bias correction, whereas MODIS and MISR provide spatial continuity and help capture regional variations. The integration of these complementary strengths enables the fused AOD product to achieve improved spatial reliability compared to using any single dataset independently. Furthermore, the approach is optimal in the geostatistical sense, as it provides the best linear unbiased estimate (BLUE) by minimizing estimation variance while incorporating satellite-derived predictors.

The revised abstract is included below:

"Synergistic fusion of aerosol parameters from multi-sensor measurements is crucial for integrating diverse data sources and generating consistent representations of aerosol distribution for accurate climate impact assessment. In this study, satellite observations from MODIS (Moderate Resolution Imaging Spectroradiometer) and MISR (Multi-angle Imaging SpectroRadiometer) are combined with ground-based measurements from Multi-Wavelength solar Radiometer (MWR) and CIMEL sun-photometers from the ARFINET and AERONET respectively to generate fused Aerosol Optical Depth (AOD) fields over India. The primary

focus of this study is to develop a fusion framework over India, involving the evaluation and comparison of two approaches Universal Kriging (UK) and novel hybrid geostatistical-machine learning approach (RK-ML). Both methods share the same geostatistical foundation (variogram-based spatial-modelling) but differ in how the mean structure of AOD is estimated. In UK, satellite-derived AOD serves as deterministic trend for spatial prediction and is effective when ground based observations are well distributed, whereas RK-ML considers SVR-predicted AOD as prior and applies Ordinary Kriging to interpolate residuals from real-time ground observations, maintaining a near-zero residual mean away from observations which reduces distortion under sparse and uneven data conditions. Our results highlight seasonal fused AOD maps (winter, pre-monsoon, and post-monsoon) over India. Leave-One-Out Cross-Validation (LOOCV) is adopted as an evaluation strategy for assessing model performance, showing that the 95% confidence interval ($\pm 2\sigma$) of the fused AOD captures over 80% of ground observations, indicating effectiveness in capturing regional aerosol variability. RK-ML demonstrates more stable spatial patterns and improved LOOCV performance compared to UK, particularly in regions with limited ground-based coverage."

Introduction:

Query-5: The use of AERONET AOD measurements is mentioned here (2nd paragraph), but not in the abstract.

Response: We have revised the abstract to explicitly include the use of both ARFIENT and AERONET observations in the study.

Section 2.1 Ground-based AOD:

Query-6: Which agency operates ARFINET? ISRO? This should be cited here.

Response: We have updated the citations in the section 2.1.

Line 168-170: "The ground-based AOD is primarily obtained from ARFINET observations, having continuous measurements across the Indian region since 1985 maintained under ISRO-GBP (Gogoi et al., 2009; Babu et al., 2013)."

Query-7: Are the measurements from MWR made simultaneously across all ten narrow wavelength filters?

Response: Yes, the measurements can be approximated as simultaneous. In exact sense, the difference between consecutive filters is ~4-5 sec and consecutive measurement from same filter is on two minute lag. A sample table of acquisition file is given below.

Date:1/ 4/ 2016					
H:MM:SS	**Filter number**	**Voltage (mV)**	**H:MM:SS**	**Filter number**	**Voltage (mV)**
Round-1			**Round-2**		
82304	**1**	**129**	**82504**	**1**	**87**
82309	**2**	**433**	**82509**	**2**	**296**
82314	**3**	**142**	**82514**	**3**	**92**

82318	**4**	**1042**	**82518**	**4**	**735**
82323	**5**	**513**	**82523**	**5**	**391**
82328	**6**	**618**	**82528**	**6**	**496**
82332	**7**	**825**	**82532**	**7**	**665**
82337	**8**	**949**	**82537**	**8**	**750**
82342	**9**	**239**	**82542**	**9**	**189**
82347	**10**	**1084**	**82547**	**10**	**865**

Query-8: Does the variance of the Langley intercept cause an uncertainty of ~ 5% in AOD derivation?

Response: We are sorry for the lack of clarity on Langley intercept. The details regarding the estimation of AOD based on Langley technique (LI) is included in the revised manuscript and the uncertainty caused by variation in LI is discussed (as given below):

Line 190-201: "The accuracy of AOD estimates from MWR is based on the accuracy of the estimate of LI. Since, LI is also a parameter of indirect calibration of the instrument, the temporal variability of LI is examined to ensure performance of the system and qualify usable data. Typically LI varies within 5% of the mean and up to 10% in worst cases. Fluctuations are more pronounced at shorter wavelengths than at longer ones. Owing to these variations, total AOD uncertainty ranges from 0.02 to 0.03, increasing at shorter wavelengths (<500 nm) and during high AOD conditions (>0.5), which are mainly limited to the pre-monsoon season. Importantly, these errors are primarily statistical and uncorrelated across channels, rather than systematic (e.g., dark current, detector offsets, and molecular scattering/absorption modelling which are <0.1%). The instrument details, AOD retrieval method, and error budget have been discussed elsewhere Gogoi et al., 2009; Babu et al., 2013; Kompalli et al., 2010; Moorthy et al., 2007)."

Query-9: A map of ARFINET operating sites would be desirable.

Response: Complied with, a map showing all ARFINET sites is included in the revised manuscript (**Fig. S1a**).

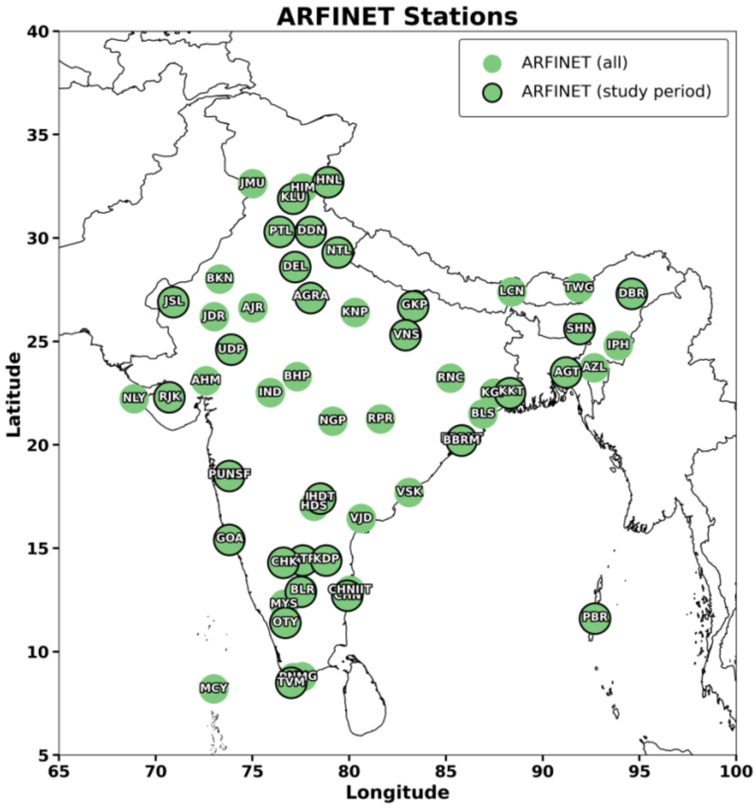

Figure – S1a. ARFINET(Aerosol Radiative Forcing over India NETwork) stations all over different parts of India (green circles represent stations while circles with black outline are the stations used for current study)

Section 2.2 Satellite retrieved AOD:

Query-10: Note that Dark Target and Deep Blue algorithm retrieve AOD using two different respective algorithms. The combined product is derived by selecting the best retrieval from either of the algorithms (i.e., DT over darker surfaces and DB over semi-arid and arid surfaces).

Response: We thank the reviewer for highlighting this important point. We have included the specific details of Dark Target and Deep Blue retrieval algorithms and in the revised manuscript to better explain that the combined AOD product that is generated by selecting the most appropriate retrieval from either algorithm (i.e., Dark Target over darker surfaces and Deep Blue over semi-arid and arid surfaces).

Line 225-233: "The merged AOD product combines only high-quality Dark Target (DT; QA = 3 over land, QA > 0 over ocean) and Deep Blue (DB; QA = 2 and 3) retrievals to provide global 10 km coverage. Over land, selection is based on Normalized Difference Vegetation Index (NDVI), with DB used for bright (arid, semi-arid) surfaces (NDVI ≤ 0.2), DT for vegetated (darker) regions (NDVI ≥ 0.3).In transitional zones, the higher-QA retrieval or their average is applied, while over ocean only DT is used. Although this approach improves spatial coverage and usability, uncertainties may arise in averaged regions and due to assumptions about algorithm performance across surface types (Sayer et al., 2014)."

2.3.2 Variogram Analysis:

Query-11: Fig S1: the detrending process is not well understood. Did author use long-term MODIS AOD datasets over India? Does this include all four seasons?

Response: Thanks for suggesting this important point. We have elaborated the discussion on detrending process in the revised manuscript. The detrending applied in this study refers specifically to removing large-scale, systematic spatial trend in the data, such as the variations arising out of the changes in elevation or latitude-based variations.

Lines 331-342: "However, real-world environmental and geophysical data often exhibit large-scale spatial trends driven by physical and geographical factors, such as latitude, longitude, and elevation. In the case of AOD, these variables act as key spatial predictors that capture dominant regional gradients and can be used to model and remove the large-scale spatial trend. In the presence of strong spatial trends, variogram may become unbounded or exhibit unrealistically large ranges. These spatial trends violate the stationarity assumption which can lead to unbounded variogram. To address this spatial detrending of the data is performed, which isolates the local fluctuations or residuals from the spatial data set. This serves as an essential step in geostatistical analysis to ensure a well-defined and bounded variogram, enabling reliable estimation of sill, nugget, and range parameters for spatial covariance modeling. To validate this assumption, we obtained the frequency distribution of satellite AOD and their residuals (Fig. S4) after detrending."

Lines 344-348: "Since the detrending in our study is purely a spatial operation, the temporal dimension is not explicitly considered and is effectively treated as constant during the detrending process. Consequently, the approach does not involve long-term datasets or explicitly account for seasonal variability (e.g., all four seasons)."

Query-12: Figure 3: Similar long-term seasonal climatology maps from MISR are wroth showing here to examine consistency or lack thereof.

Response: Complied with. Following this recommendation, we have included the long-term seasonal climatology map derived from MISR, similar to the MODIS map, in **Figure 3b** to facilitate comparison and to examine the consistency between the two datasets.

Line 558-560: "The spatial patterns of a decadal average satellite-based MODIS and MISR AOD (2011–2020; Fig. 3a, 3b) also shows persistent high AOD values in the IGP and its outflow regions across all seasons."

Line 578-583: "Additionally, discrepancies between MODIS and MISR AOD are also seen owing to fixed and multi angle retrievals especially in Pre-monsoon period over the NW region, where MISR AOD is significantly different from MODIS. There are also some pockets where low AOD region observed by MODIS is alternatively represented as a region of higher AOD in MISR observations, particularly in proximity to the IGP outflow."

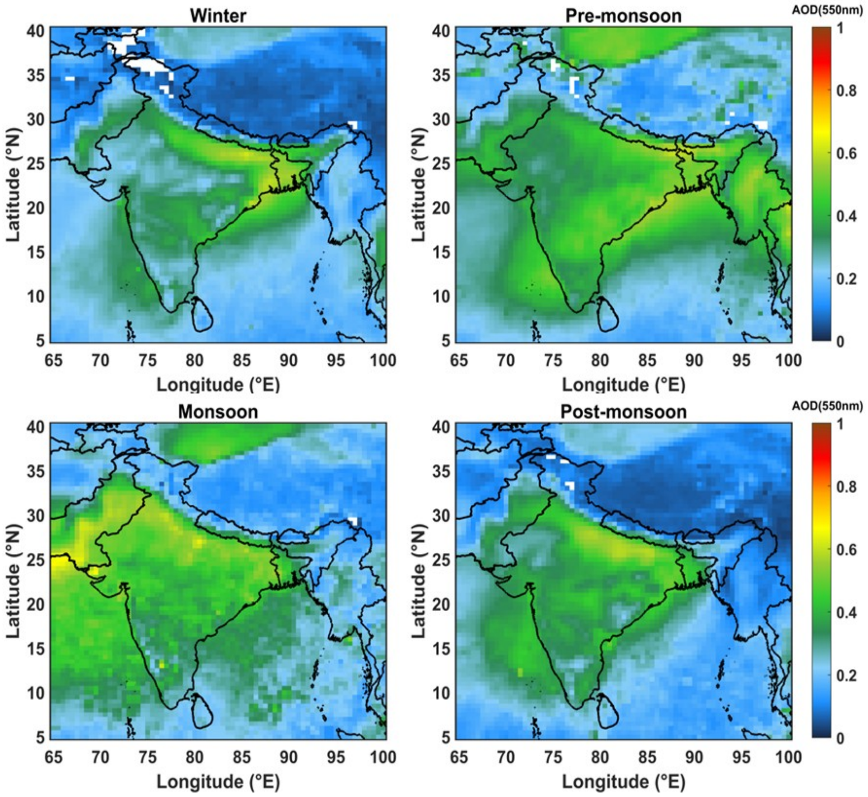

Figure 3b. Long term (2011-2020) satellite based AOD (at 550 nm) from MISR over south-Asian region.

3.2 Inter-comparison of satellite-ground AOD

Query 13: Lines 466-473: This description appears belonging to Figures S7-S9, not S4-S6. Please check and verify. Also, add a brief discussion on satellite vs. ground AOD comparison (MISR underestimates ground AOD at moderate to high aerosol loadings).

Response: We thank the reviewer for pointing this out. We have corrected the relevant text corresponding to Figs. S8–S10 and S11–S13 in the revised manuscript, quantitatively describing the association between satellite and ground-AOD.

Line 621-629: "The scatter plots (Supplementary Figs. S8-S10; the number of ground stations included in the correlation studies is given in Table 1) between MODIS/ MISR and ground-based AOD highlight moderate to strong correlations (~ 0.8-0.9) in winter (January) and post-monsoon (November), while moderate correlations (~0.54-0.77) between the two are observed in pre-monsoon (May). The RMSE between MISR and ground-based AOD is higher (≥ 0.2) during winter and post-monsoon, whereas higher RMSE values between MODIS and ground-based AOD are observed during the pre-monsoon period. The prominent locations contributing to mean errors and weak correlations with ground observations are situated in the NW and IGP regions."

Line 630-637: "The quartile-plots (Figs. S11-S13) highlight significant spatio-temporal variability in AOD, with both sensors displaying higher AOD over terrestrial regions, particularly in the IGP, its outflows, and South (Peninsular) and Central India. The third and fourth quartiles are more representative for AOD over land regions than in surrounding areas like oceans and elevated terrain. Data with respect to longitude and latitude show that higher AOD values are mostly confined to 20°-30°N latitude and 80°-95°E longitude. However, MODIS consistently recorded significantly higher AOD values than MISR, with notable dissimilarities in quartile patterns over northern India during May."

Line 638-649: "Both the correlation and quartile analyses highlight the advantages and limitations of MODIS and MISR observations. For example, MISR tends to underestimate high AOD conditions in urban regions compared to MODIS, even though it can effectively separate surface contributions under low aerosol loading, as also reported by Tao et al. (2020). Under high AOD conditions, the benefit of multi-angle measurements becomes limited, as thick aerosol layers smooth out surface reflectance signals (BRDF), potentially leading to an underestimation of AOD due to misattribution of aerosol contributions to surface reflectance. In contrast, when dust loading is dominated by coarse and non-spherical particles (in May), MISR demonstrates relatively better performance than MODIS (as shown by scatter plots). This difference may be attributed to the advantage of MISR's multi-angle observation capability, consistent with findings from Middle Eastern validation studies (Farahat, 2019; Garay et al., 2017)."

Query 14: Lines 495-503: This paragraph should go to the beginning of the section 3.2 (also change Figure numbers S7-S9 to S4-S6).

Response: Changes have been made as suggested.

Section 3.3.3

Query 15: Up to this point, it was unclear whether daily or monthly MODIS/MISR dataset is used in the fusion process. It looks like monthly datasets are used. Please confirm.

Response: Thanks for the suggestion, we have clearly mentioned the use of monthly data sets in the beginning (Section **2.3.1)** while discussing about collocation approach.

-END