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Advancing Aerosol Measurement Traceability, AI and Machine Learning, Regulatory Standards, and Cross-Disciplinary Harmonization for Climate Change and Sustainability

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ABSTRACT

Aerosols exert diverse influences on human health, agriculture, air quality, and climate systems. Despite continuous progress in aerosol measurement technologies and methodologies, significant uncertainties persist in quantifying their physical properties across many applications. Accurate characterization of airborne particles particularly in terms of number and mass concentrations, size distributions, and light adsorption properties is essential for understanding their atmospheric behavior and environmental fate. This study evaluates the physical properties of aerosols with a focus on measurement protocols and documentary standards that ensure traceability and enable interoperability of data obtained using different instruments across spatial and temporal scales. To enhance awareness and highlight inconsistencies in measurement practices across aerosol science subfields, existing standards and regulatory frameworks related to air quality and particle emissions from transportation (automobiles, aviation, shipping) and stationary sources are critically reviewed. Emphasis is placed on the urgent need for harmonization of measurement methodologies, supported by specific examples and practical recommendations. Owing to its comprehensive treatment of aerosol measurement practices and documentary standards across multiple disciplines, this review serves as a valuable reference for researchers and policymakers seeking to improve measurement accuracy and

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consistency.

Keywords: Atmospheric aerosols: Nanoparticles; Health impacts; Climate change; Radioactive aerosols, Exposure assessment.

Highlights

- Presents a detailed report of atmospheric aerosols sources, nanoparticles origins, and measurement methodologies.
- Investigations into the impacts of aerosol nanoparticles on human health and ecosystems, supported by in vivo and laboratory-based studies.
- Examine the role of aerosols in climate change, including interactions with solar radiation and renewable energy systems.

1. Introduction

Atmospheric aerosols, a key element of the atmosphere, consist of suspended solid or liquid particles. These aerosols play a major role in influencing both regional air quality and broader environmental and climate changes (Schwartz and Andreae, 1996; Menon et al., 2002; Ackerman et al., 2004). Since atmospheric particles typically remain in the air for only a few days up to a week, the earth-atmosphere system relies heavily on both their emission and long-range transport. The optical properties of aerosols, which primarily control atmospheric radiation, provide essential information for predicting global climate change and assessing related responses (Hansen et al., 1997; Holben et al., 1998; IPCC, 2007, 2013). A key parameter in this context is aerosol optical depth (AOD), which quantifies the columnar extinction caused by aerosol and the overall reduction of solar radiation (Breon et al., 2002). Shifting from fossil fuels to low-carbon energy sources such as renewable energy is a critical strategy to mitigate the most severe impacts of climate change (IPCC, 2021). Renewable energy, derived from resources like sunlight, wind, biomass, and water-which are all affected by weather and climate-is widely recognized as an effective decarbonization approach. As of 2022, 95% of the global 3.37 TW of installed renewable energy capacity came from wind, solar, and hydropower. In that year, Asia and Europe contributed 232 GW of new capacity, representing roughly a 10% annual increase, while regions including North America, South America, and Africa experienced slower growth rates ranging from 4.8% to 7.4%. By the close of 2022, 83% of all newly added power generation capacity was from renewable sources. The ongoing integration of renewable energy into the global energy mix will increasingly be shaped by weather patterns and climate events (Kumler et al., 2019; Craig et al., 2019; Carreno et al., 2020). Climate change itself persists due to the inertia of the climate system, even in scenarios involving significant reduction in greenhouse gas emissions (Tebaldi et al., 2013). Additional impacts include variations in agricultural productivity, fluctuations in natural resources and drought occurrence (Ohba et al., 2023; Doss Gollin et al., 2023), alterations in water availability (Konapala et al., 2020), and increased frequency and intensity of extreme weather events such as hurricanes (Knutson et al., 2021). In summary, while renewable energy serves as key mitigation pathway for climate change, it is also inherently sensitive to climatic variability. Consequently, over the past decade research efforts have focused on evaluating the potential impacts of climate changes on renewable energy systems. These studies examine both the meteorological drivers underpinning renewable energy resources and the influence of different climate scenarios on energy production within operational planning horizons. Aerosols can modify both the optical

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and microphysical properties of clouds, and numerous studies have utilized aerosol parameters to evaluate their effects on radiation balance, cloud formation and precipitation process.

The primary techniques for monitoring aerosol optical properties across the atmospheric column include satellite-based and ground based remote sensing (Pozzer et al., 2015; Zhao et al., 2017; Hammer et al., 2018; Che et al., 2019). Ground-based observations provide highly accurate and direct measurements of columnar optical properties and are widely regarded as reliable reference methods. Global monitoring networks have been established to collect long-term aerosol data at national, regional, and global scales (Knutson et al., 2021; Ohba et al., 2023; Doss-Gollin et al., 2023). Satellite remote sensing complements ground-based observations by providing broader spatial and temporal coverage, thereby addressing inherent limitations in ground-based monitoring (Kosmopoulos et al., 2008; Sogachevaet et al., 2018). Equipped with advanced sensors, satellites can generate high-resolution global datasets on aerosol optical properties, enabling detailed analysis of their spatial and temporal variability (Konapala et al., 2020; Olesen et al., 2011; Kanoglu et al., 2020). Overall, aerosols originating from both natural and anthropogenic sources can significantly influence atmospheric temperature, ecological systems, and weather patterns at both regional and global scales. Their key optical properties, obtained through integrated observational and modelling approaches, provide critical insights into their evaluation and impacts. Investigations of aerosol-climate feedback mechanisms, particularly from the perspective of optical radiation interactions, form a crucial scientific basis for understanding aerosol-related environmental and climatic effects. Such studies also elucidate the role of regional transport in shaping the optical properties of both natural and anthropogenic aerosols, thereby supporting environmental monitoring and climate change assessments.

2. Atmospheric Aerosols: Sources, Characteristics, Health and Ecosystem Impacts, and Machine Learning-Based Forecasting

2.1. Machine Learning Models for Atmospheric Aerosol Forecasting

Machine learning (ML) has become increasingly useful for forecasting atmospheric particulate matter because air-quality datasets often contain complex and nonlinear relationships. Compared with conventional statistical approaches, ML models can process large environmental datasets and capture interactions among pollutant concentrations, meteorological conditions, and temporal patterns (Fazzini et al., 2023; Plocoste and Laventure, 2023). However, their reliability depends strongly on data quality, model selection, hyperparameter optimization, and control of overfitting (Elgeldawi et al., 2021). Extreme Gradient Boosting (XGBoost) is a tree-based ensemble algorithm widely applied to environmental prediction. It combines multiple decision trees and uses regularization to control model complexity and reduce overfitting. Its ability to capture nonlinear relationships and process large datasets makes it suitable for particulate-matter forecasting (Chen and Guestrin, 2016; Gonzalez et al., 2018). Categorical Boosting (CatBoost) is another gradient-boosting approach that uses ordered boosting and can efficiently recognize complex patterns within environmental datasets. Regularization and optimization options allow the model to be adapted to different monitoring locations and datasets (Mampitiya et al., 2023). Long Short-Term Memory (LSTM) is a recurrent neural-network architecture particularly suited to time-series data. Its memory cells and input, output, and forget gates allow information from previous time steps to influence subsequent predictions. This capability is useful for

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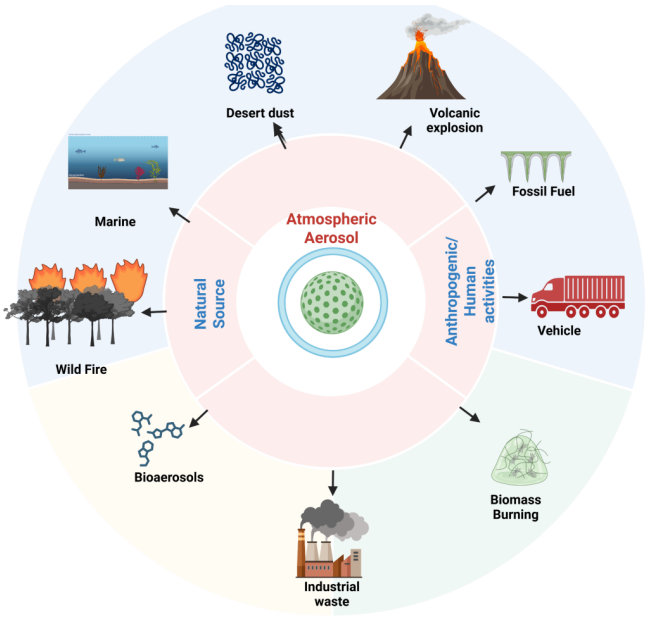


Figure 1. Sources of atmospheric aerosols: natural and anthropogenic contributions. Schematic illustration depicting the diverse sources of atmospheric aerosols, categorized into natural and anthropogenic origins. Natural sources include desert dust, marine emissions, wildfires, volcanic eruptions, and bioaerosols, while anthropogenic sources arise from human activities such as fossil fuel combustion, vehicular emissions, biomass burning, and industrial waste. The central representation of atmospheric aerosol highlights the integration of these sources, emphasizing their combined influence on atmospheric composition and environmental processes..

atmospheric monitoring because pollutant concentrations frequently exhibit temporal and diurnal patterns (Hochreiter and Schmidhuber, 1997).

Bidirectional LSTM (Bi-LSTM) extends conventional LSTM by processing sequential information in both forward and backward directions. This provides additional temporal context and can improve pattern recognition in complex time-series datasets (Graves and Schmidhuber, 2005). Artificial Neural Networks (ANNs) identify relationships among input and output variables through interconnected computational layers. Their flexibility makes them useful for modeling nonlinear environmental processes, although appropriate architecture selection, cross-validation, regularization, and early stopping are important for controlling overfitting (Novitski et al., 2022).

Ensemble models combine predictions from multiple algorithms rather than relying on a single model. This approach can improve robustness because individual algorithms may capture different characteristics of the same dataset (Ghosh et al., 2023). The uploaded study, for example, combined ANN and Bi-LSTM predictions within its ensemble architecture and found that the best-performing algorithm varied among monitoring locations. These ML approaches have demonstrated considerable potential for atmospheric aerosol monitoring and short-term forecasting. In the Republic of Ireland study, XGBoost, CatBoost, ANN, LSTM, Bi-LSTM, and ensemble models were trained and optimized for location-specific PM_{10} prediction, with hyperparameter tuning used to adapt individual algorithms to different monitoring sites. Such approaches could eventually complement aerosol measurement, spectroscopic and remote sensing (SRS), sensor networks, and environmental surveillance, although their extension to atmospheric radionuclides would require radionuclide-specific datasets and validation. Atmospheric aerosols consist of fine solid or liquid particles suspended in air, with sizes ranging from a few nanometers to several micrometers (Kumler et

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al., 2019, 2025; Craig et al., 2019). They are integral to atmospheric processes due to their influence on air quality, weather systems, and climate dynamics (Karnauskas et al., 2018; Soden et al., 2002; Gernaat et al., 2021). Aerosols originate from both primary sources' direct emissions from phenomena such as dust storms, volcanic eruptions, and industrial activities and secondary processes involving chemical transformations in the atmosphere, such as gas-to-particle conversion (Figure 1) (Carreno et al., 2019; Tebaldi et al., 2013; Knuston et al., 2021). Aerosol nanoparticles, also referred to as ultrafine particles (UFPs), represent a critical subset of aerosols with diameters below 0.1 μm. Their small size and high surface-area-to-volume ratio enhances their chemical reactivity and capacity to absorb toxic substances, making them particularly significant for environmental and health considerations (Canty et 2013; Parker and Irvine, 2018). These particles influence the Earth's radiative balance by scattering and adsorbing solar radiation, thereby contributing to both atmospheric warming and cooling effects. Their atmospheric distribution and fate are governed by complex processes, including emission, chemical transformation, transport, and removal mechanisms such as precipitation (Namasivayam et al., 2024; Irvine et al., 2016; Baur et al., 2024). Naturally occurring aerosols- including volcanic emissions, marine aerosols, mineral dust, and bioaerosols- each play distinct roles in atmospheric composition and climate processes. Volcanic aerosols, particularly sulphate particles, can remain the stratosphere for extended periods and induce temporary surface cooling. Marine aerosols, generated through sea spray and oceanic biological activity, contribute to cloud formation and climate regulation. Mineral dust, primarily originating from arid regions such as the Sahara, facilitates long-range nutrients and influences both cloud microphysics and radiative balance. Bioaerosols- incluiding microorganisms, spores, and pollen- can travel over large distances and impact atmospheric processes, agriculture, and public health (Namasivayam et al., 2024; Dagon and Schrag, 2019; Cheng et al., 2019).

Algorithms such as artificial neural networks, tree-based models, recurrent neural networks, and ensemble methods can integrate large environmental datasets and identify relationships that may be difficult to represent using conventional statistical approaches. This data-driven transition is consistent with broader developments across environmental science, where integrated assessment is increasingly required to understand pollutant sources, transport, exposure, and environmental risks across interconnected air, soil, and water systems (Singh et al. 2025; Natishah et al. 2025). Advances in sustainable materials also demonstrate opportunities to connect environmental monitoring with technological solutions; for instance, PET-derived carbon nanomaterials have been investigated for green-energy and environmental-remediation applications, while smart polymer systems have been explored for integrated water management (Pusuluru et al. 2026a,b). Similarly, studies addressing water-quality variability and uranium solubility illustrate the importance of considering physicochemical conditions when evaluating contaminant mobility and environmental fate (Pusuluru et al. 2026c; Punna et al. 2026a). Although these studies address different environmental compartments, collectively they emphasize the value of combining reliable measurements with multidisciplinary datasets for predictive environmental assessment.

The expanding application of AI and ML in energy, materials, and environmental systems provides additional opportunities for aerosol forecasting and sustainability research. AI-integrated manufacturing has demonstrated how computational approaches can support the development and optimization of advanced

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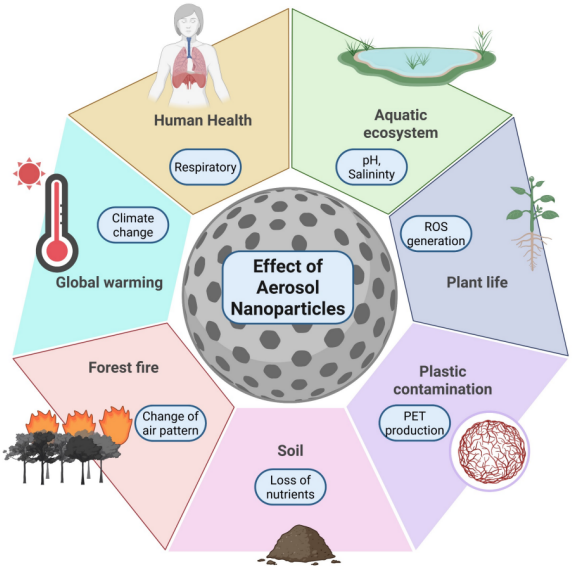


Figure 2. Environmental and health impacts of aerosol nanoparticles.Schematic illustration summarizing the multifaceted effects of aerosol nanoparticles on environmental systems and human health. The central node represents aerosol nanoparticles, with surrounding sectors highlighting key impact domains: human health (respiratory effects), aquatic ecosystems (alterations in pH and salinity), plant life (reactive oxygen species (ROS) generation), plastic contamination (association with polymer production such as PET), soil systems (nutrient loss), forest fire dynamics (changes in air patterns), and global warming (contribution to climate change). The figure emphasizes the interconnected nature of nanoparticle-induced impacts across atmospheric, terrestrial, and biological systems..

materials for energy storage, catalysis, and environmental applications (Punna et al. 2026b), while AI-driven microalgal systems have connected data-based optimization with green fabrication, bioenergy production, sustainable materials, and biowaste valorization (Abbaszadeh et al. 2026). Machine-learning-assisted technoeconomic assessment has further demonstrated the ability of computational models to compare complex biofuel-production pathways and support technology and sustainability decisions (Singh et al. 2026). In parallel, optimization of algal biorefineries illustrates how AI-based approaches can be combined with process optimization and sustainability assessment to improve renewable-resource utilization (Pusuluru et al. 2026d). These cross-disciplinary advances provide a useful foundation for atmospheric applications, where validated ML models could integrate aerosol measurements, meteorological observations, emission information, sensor networks, and historical records to improve concentration forecasting, source assessment, exposure evaluation, and early-warning systems. Such integration can ultimately strengthen the connection between measurement traceability, predictive aerosol monitoring, climate-change assessment, and sustainable environmental management.

2.2. Aerosol Nanoparticles and Measurements

Aerosol nanoparticles, or ultrafine particles (PM0-1), are particles with diameters below 100 nm that may exist in solid, liquid, semi-volatile, or low-volatility forms (Figure 2). Their formation occurs through both primary emissions-such as biomass combustion, fossil-fuel burning, and industrial activities-and secondary atmospheric reactions involving precursors like VOCs, SO2, and NOx. Due to their small size, these particles can remain suspended in the atmosphere for extended periods and undergo long-rang transport (UNEP, 2023; Gokmen et al., 2016; Romero et al., 2014). Their potential health risks are significant as they can penetrate biological barriers and reach sensitive regions within the human body. Chemically, they exhibit considerable

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complexity, comprising carbonaceous materials, trace materials, trace metals, sulphate, nitrates, and diverse organic compounds. Studies conducted across Asia highlight key compositional features, including the presence of PAHs, elevated PM2.5 concentrations during dry seasons, and the formation of nitro-oxy compounds and organosulfates under urban photochemical conditions. The presence of light-absorbing species such as black carbon (BC) and brown carbon (BrC) is particularly important due to their role in atmospheric heating through solar radiation adsorption (Namasivayam et al., 2024). The measurement of aerosol nanoparticles requires advanced and highly sensitive instrumentation due to their small size and chemical complexity. Techniques (DC) and scanning mobility characteristics (AL-Rasheedi et al., 2020; Conceicao et al., 2018; Zamuda et al. 2023; Wild et al., 2015). Chemical composition can be analyzed using instruments such as FIGAERO-CIMS and Aerosol Mass Spectrometry (AMS), which provide detailed profiling of both organic and inorganic constituents. Optical properties are assessed using methods including remote sensing, photoacoustic spectroscopy, and refractive index measurements. Ballon-borne instruments enable the study of vertical aerosol distributions, while modern platforms such as SKYNET and modular air quality monitoring systems support real-time ambient measurements. Despite these advances, challenges remain in terms of sensitivity, spatial resolution, and temporal variability, necessitating further development of robust and scalable measurement techniques (Namasivayam et al., 2024).

2.3 Aerosol Nanoparticles Impact on Health & Ecosystem

Aerosol nanoparticles pose significant risks to both human health and ecological systems. Their small size and high reactivity enable deep penetration into the alveolar regions of the lungs, entry into the bloodstream, and transport to vital organs (Sawadogo et al., 2020; IPCC, 2021; Crook et al., 2011; McVicar et al., 2012). Associated health impacts include cardiovascular diseases, neurological disorders such as Alzheimer's disease, respiratory conditions including asthma and chronic obstructive pulmonary pronounced in urban and industrial environments with elevated pollution levels. Bioaerosol, including fungal spores, can further contribute to respiratory and gastrointestinal health issues, especially in immunocompromised individuals (Cherian and Quaas, 2020). In ecological systems, aerosol nanoparticles can exert both beneficial and detrimental effects on plant growth. While they may enhance nutrient availability under certain conditions, they more commonly induce oxidative stress, inhibit seed germination, and damage plant tissues. In aquatic environments, aerosols can alter water chemistry, reduce light penetration, and disrupt primary productivity. Accumulation of nanoparticles in aquatic organisms can lead to DNA damage and changes in gene expression. In soil systems, nanoparticles influence microbial community dynamics, reduce nutrient availability, and impair soil fertility. These impacts collectively affect ecosystem functioning, food webs, and biodiversity (Namasivayam et al., 2024).

2.4. In Vivo or Laboratory Scale Generation of Aerosol Nanoparticles

Laboratory-scale generation of aerosol nanoparticles is commonly achieved through controlled combustion of biomass materials such as wood pellets, rice husk, and agricultural residues. Experimental conditions-including gas flow rates, sampling parameters, and combustion temperatures-are carefully regulated to influence nanoparticle formation. Particles produced under these conditions are collected using specialized instruments such as nano samplers and Andersen sampling. Analytical techniques include Thermogravimetric Analysis (TGA) and Differential Thermal Analysis (DTA)

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are employed to evaluate thermal behavior and particle generation characteristics. The resulting nanoparticles exhibit physiochemical properties that depend on factors such as biomass type, heating rate, combustion efficiency. These laboratory-generated particles are also being explored for potential biomedical applications, including drug delivery, diagnostics, and treatment of respiratory diseases. For example, engineered aerosol nanoparticles can facilitate targeted drug delivery to the lungs, offering improved therapeutic outcomes for conditions such as asthma and cystic fibrosis. However, this field remains in an early stage of development, and further research is required to assess scalability, performance, and safety considerations (Namasivayam et al., 2024).

3. Intersection of Climate Changes, Solar Radiation Modification and Renewable Energy

The convergence of climate change, solar radiation modification (SRM), and renewable energy research has become increasingly significant as global energy systems shift toward low-carbon alternatives. Ongoing climate changes is already modifying key meteorological parameters-including solar irradiance, wide velocity, precipitation regimes, and temperature-which directly influence the performance, efficiency, and reliability of renewable energy technologies such a solar, wind hydropower, and bioenergy. Concurrently, SRM approaches, particularly stratospheric aerosol injections (SAI) (Wild et al., 2017; Dutta et al., 2022; Chen, 2021; Craig et al., 2018). Proposed as a geoengineering strategy to reduce global temperature by reflecting incoming solar radiation, may substantially alter these same climatic variables, either mitigating or intensifying climate-induced effects. For example, SRM implementation may decrease the availability of direct solar radiation required for concentrating solar power (CSP), modify atmospheric circulation patterns that govern wind energy generation, and influence hydrological cycles critical for hydropower systems. Despite these far-reaching implications, current understanding remains constrained by substantial uncertainties in climate modelling especially regarding cloud processes, aerosol interactions, and region-specific climate responses (Feron et al., 2021; Watson Parris et al., 2022; Zelinka et al., 2023). Addressing these challenges necessitates the development of advanced climate models with enhanced spatial and temporal resolution, improved representation of atmospheric processes, and integration with renewable energy performance frameworks. The establishment of standardized evaluation metrics is also essential to ensure consistent comparison of renewable energy outcomes across different climate and SRM scenarios (Intergovernmental Panel on Climate Change. Clouds and aerosols, 2014). Furthermore, comprehensive observational datasets derived from satellite missions and atmospheric field campaigns are critical for model validation and improving predictive capabilities (Kiehl, 2007; Schuddeboom and McDonald, 2021; Zhao et al., 2022). In addition, research must incorporate governance, equity, and socioeconomic considerations, as SRM interventions may produce uneven regional consequences, potentially advantage certain regions while disadvantage others. Evaluating the long-term impacts of SRM on hybrid renewable systems-such as co-located solar-wind installations-is also crucial for ensuring energy security and infrastructure resilience. Overall, addressing these complexities requires coordinated, multidisciplinary global research efforts to effectively manage uncertainties and algin climate intervention strategies with sustainable energy objectives (Kumler et al., 2025).

6. Conclusion

Aerosols originating from both natural processes and anthropogenic activities exert significant

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influences on weather, climate systems, environmental quality, ecological balance, and human health at regional and global scales. The acquisition of long-term, high-quality measurements of key aerosol optical radiation parameters, along with the analysis of their spatial and temporal variability, provides a critical scientific basis for advancing understanding of their climatic environmental impacts. This report has expanded the investigation of aerosol-climate and aerosol-weather feedback mechanism from the perspective of optical radiation characteristics, while also identifying the contributions of regional transport to both natural and anthropogenic aerosol sources. The findings offer essential scientific support for climate change research, air pollution mitigation, and environmental monitoring efforts. Potential transport pathways of Asian dust-from regions such as the Gobi and Taklimakan deserts to the Arctic-have been examined using inversion techniques applied to AOD data derive from multiple satellite remote sensing platforms. Relationships between particular matter concentrations and AOD, as well as between cloud effective radius and AOD, have also been analysed. Aerosol component concentrations can be directly retrieved from radioactive measurements or estimated using ground-based aerosol optical observations. Quantitative analyses reveal the spatial and temporal variability of aerosol direct radiative effects across different regions, including their heating and cooling influences on the Earth-atmosphere system. Strong atmospheric absorption has been shown to alter thermodynamic conditions through aerosol radiative forcing. Dust particles with significant optical absorption properties can modify the balance of incoming and outgoing radiation, influence atmospheric heating rates and thereby affect weather patterns and climate processes. Furthermore, the study evaluates how aerosol scattering and absorption properties influence radiation balance and cloud-precipitation interactions across different regions. Advanced machine learning techniques have been employed to extract patterns in aerosol distribution and variability from large-scale remote sensing datasets. In particular, deep learning approaches leveraging diverse neural network architecture demonstrates strong potential for improving the estimation of aerosol impacts on the earth-atmosphere system and enhancing understanding of the underlying physical processes.

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S.S. (Showparnickaa Subburao): Led the conceptualization of the study and played a primary role in developing the overall framework of aerosol measurement traceability and cross-disciplinary harmonization. Contributed extensively to literature report, data synthesis, and drafting of the manuscript.

R. (Ravichandran): Contributed to the analysis of regulatory standards and environmental frameworks related to aerosol measurement. Assisted in structuring the manuscript and reviewing key technical sections.

D.S. (Dharshini Srinivasan): Supported data collection and compilation of literature related to aerosol properties, measurement techniques, and environmental impacts. Assisted in manuscript preparation and formatting.

A.J.N. (A.J Natishah): Contributed to the evaluation of measurement methodologies and supported the integration of interdisciplinary perspectives within the manuscript.

I.S.M. (Indumathi S.M.): Supervised the study, provided critical insights into research design and content development, and contributed to manuscript report and final approval.

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S.K.P. (Sai Kumar Punna): Assisted in technical analysis related to material characterization and contributed to the interpretation of aerosol measurement techniques and associated standards.

S.P. (Suvarshitha Pusuluru): Contributed significantly to data analysis, synthesis of cross-disciplinary insights, and development of sections related to standardization and harmonization. Played a key role in manuscript drafting and revision.

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