Latent Space Atmospheric Particulate Science

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ABSTRACT: Airborne particulate matter is a major contributor to global illness and originates from a range of natural and anthropogenic sources. These particles can undergo agglomeration, whereby individual units cluster into larger, structurally complex assemblies. This process can span multiple spatial and temporal scales, from nanometer-sized particles interacting over seconds to minutes, to the formation of larger aggregates that form and evolve over hours or days. Understanding how particles agglomerate and transport is essential for accurately predicting their dispersion, environmental impact, and potential health risks. However, traditional analytical models struggle to capture the multivariate, nonlinear nature of these processes. Recent advances in deep learning, in particular the use of latent space representations, offer promising new tools for addressing this complexity. More specifically, latent spaces allow high-dimensional data, such as particle morphology and spatiotemporal measurements, to be projected into lower-dimensional manifolds where hidden structure and dynamics may become more interpretable. In this work, I explore how latent space methods could be applied to model particle agglomeration and its evolution over space and time, providing an alternative framework for understanding aerosol behavior beyond conventional techniques.

SIGNIFICANCE STATEMENT: This work proposes how advanced computational techniques can simplify the complex patterns of airborne particles by converting high-dimensional data into more manageable forms. By employing these methods to identify patterns in how particles group together, new insights into the behavior of air pollution within the atmosphere could be obtained. This is significant because these techniques could lead to models to be developed that can improve air quality forecasts and inform public health strategies. Additionally, this work suggests that integrating these techniques with multiple data sources could further enhance our understanding of how pollutants form and evolve over time in the atmosphere, ultimately helping society better predict and mitigate the impacts of air pollution.

KEYWORDS: Air pollution; Pollution; Deep learning; Atmospheric composition; Atmosphere

1. Introduction

Airborne particulate matter (PM) pollution is a global health issue linked to respiratory and cardiovascular diseases and cancer (Holgate 2017; Peters et al. 2019). Recent studies have demonstrated that long-term exposure to PM2.5 and PM10 particles can significantly harm human health. A World Health Organization (WHO)-led research (Orellano et al. 2024) pooled over 100 cohort studies and demonstrated significant positive associations between PM exposure and cardiovascular and respiratory mortality. Lelieveld et al. (2020) estimated that ambient PM2.5 causes approximately 8.8 million premature deaths globally each year, reducing life expectancy by about 2.9 years. Krittanawong et al. (2023) described how chronic PM2.5 exposure promotes hypertension, oxidative stress, atherosclerosis, and systemic inflammation, which all contribute to myocardial infarction, stroke, heart failure, and arrhythmia. Wang et al. (2023) found that long-term PM2.5 exposure increased the risk of developing pneumonia by 6%, and Ni et al. (2024) showed that nearly one-third of global asthma cases (especially in children) are attributable to PM2.5. In a study by Thaichana et al. (2025), it was found that maternal exposure to high PM2.5 levels doubled the odds of preterm birth and low birth weight, with elevated risks observed even at lower exposure levels, suggesting there is no safe threshold. These results highlight that long-term PM2.5 and PM10 exposure increases mortality, exacerbates cardiovascular and respiratory diseases, and adversely affects fetal and early life development.

Particulate matter can range in size from submicron to tens of microns, existing in different shapes (Ličbinský et al. 2010) and being composed of various chemicals (Nriagu 1989). Ultrafine PM ($<$0.1-μm aerodynamic diameter), a subset of PM2.5 ($<$2.5-μm diameter), can grow larger in the presence of water vapor (Raes et al. 2000). This occurs via mechanisms that can be broadly categorized into nucleation, condensation, coagulation, and chemical reactions (Tomasi and Lupi 2017; Vehkamäki and Riipinen 2012). Nucleation refers to the formation of new particles from gaseous precursors when vapor concentrations exceed a threshold. Condensation involves the addition of gas-phase molecules to existing particles, promoting growth. Coagulation merges particles through collisions, reducing their number but increasing size, while chemical reactions, in the gas phase or on particle surfaces, can alter aerosol composition and properties.

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WHO guidelines for 24-h particulate matter concentrations are 25 μg m^{-3} for PM2.5 and 50 μg m^{-3} for PM10 (<10-μm diameter), with annual guidelines of 5 and 20 μg m^{-3}, respectively (World Health Organization 2006). Particulate matter can include pollen grains that can cause allergic rhinitis (McInnes et al. 2017) and sinusitis (Khanna and Gharpure 2012). PM2.5 can reach deep into lungs, leading to respiratory diseases such as chronic obstructive pulmonary disease (COPD) (Doiron et al. 2019), asthma (Guarnieri and Balmes 2014), and lung cancer (Raaschou-Nielsen et al. 2013), and affect the cardiovascular system (Du et al. 2016), while ultrafine particles can enter the lungs and circulation system, having been found in brain and heart tissue (Maher et al. 2016; Calderón-Garcidueñas et al. 2019).

In urban environments, airborne particulates mainly originate from diesel combustion in vehicles (Zuurbier et al. 2010), producing materials like black carbon and polycyclic aromatic hydrocarbons (PAHs) (Cadle et al. 1999). Fossil fuels (Venkataraman et al. 2005), biofuels (Bond et al. 2013), and wood burning can also contribute atmospheric particulate concentrations (Maenhaut et al. 2016). Brake and tire wear from vehicles generate rubber and metallic particulates (Thorpe and Harrison 2008). Other sources of PM include steelworks (Mazzei et al. 2008) and cement factories (Al-Neaimi et al. 2001), while natural sources include pollen and fungal spores (Isiugo et al. 2019). Indoor pollution can arise from cooking (Dacunto et al. 2013), deodorants (Park et al. 2017), smoking and incense (Li et al. 2017), as well as wood burning stoves (Chakraborty et al. 2020).

Beyond urban environments, particulate matter encompasses a diverse array of aerosol types, including natural sources such as mineral dust (Miller-Schulze et al. 2015), wildfire smoke (Meng et al. 2025), sea salt, and volcanic ash (Akinyoola et al. 2024). These aerosols vary widely in size, composition, and origin. For instance, mineral dust particles rich in silicon and aluminum can be lifted into the atmosphere from arid regions such as the Sahara Desert (Bozlaker et al. 2013). Sea salt aerosols composed primarily of sodiumchloride are generated by the action of wind on ocean surfaces. Wildfires can release smoke containing organic particles such as black carbon, impacting air quality over vast areas, while volcanic eruptions can emit ash and sulfur dioxide, leading to the formation of sulfate aerosols in the atmosphere (Langmann 2014). With this consideration, this manuscript aims to discuss how latent space models could accurately capture common structural features across heterogeneous particle sources. The methodology aims to facilitate the development of unified representations of particles originating from both natural and anthropogenic processes, thereby advancing comprehensive modeling of atmospheric particulate matter dynamics.

Aerosol particles often exhibit irregular shapes that can be characterized using fractal dimensions, which quantify their geometric complexity. For instance, fly ash particles typically display both structural fractal features, while soil dust particles tend to show primarily textural fractality (Kindratenko et al. 1994). These fractal patterns, which repeat at various scales, offer a powerful way to describe self-similar structures in natural and industrial aerosols. Fractal analysis enables (Sorensen 2001; Xiong and Friedlander 2001) researchers to distinguish between particle types with similar chemical compositions by focusing on morphological differences, thus contributing to improved environmental monitoring and pollution source attribution. Techniques such as scanning electron microscopy (SEM) combined with energy-dispersive X-ray (EDX) spectroscopy allow for detailed characterization of both particle shape and elemental composition (Heredia Rivera and Gerardo Rodriguez 2016). Owing to the complexity of particles, relying solely on simplified spherical models fails to address the true complexity of aerosol particles, which may include ellipsoids, chains, or fibrous forms. In situ imaging and analysis, therefore, provide a more accurate representations of these structures to help understand the particle behavior and thus environmental impact.

The characteristics of particulate matter, including its size, shape, and composition, along with meteorological factors, play a significant role in determining its number density and toxicity (Kelly and Fussell 2012). Therefore, it is crucial to accurately characterize and understand how these airborne particles form. This understanding not only aids in assessing the prevalence of particulate matter and its potential health implications but also provides insights into its possible sources. Furthermore, this knowledge can guide strategies to mitigate the impact of particulate matter on our health and environment (Zhang et al. 2018). Traditional particulate monitoring methods, such as the use of large filters and spore traps (Levetin et al. 2000; Peel et al. 2014), are designed to sample airborne particles and use laboratory-based postprocessing for detailed examinations.

The agglomeration of urban particulate matter has been studied using techniques such as Fourier transform infrared (FT-IR) spectroscopy and EDX spectroscopy (Zeb et al. 2018), as well as electron microscopy (Yao et al. 2009). Laser-induced breakdown spectroscopy (LIBS) also offers powerful elemental characterization of individual particles and has been applied to particles from industrial sources for real-time monitoring (Gallou et al. 2011). However, owing to its high cost, limited spatial coverage, and operational complexity, LIBS is currently impractical for widespread urban or atmospheric sensing applications.

While it is recognized that particulate matter can originate from primary sources or through atmospheric agglomeration processes (Seinfeld and Pandis 2016), the precise mechanisms that lead to the formation of PM are not yet fully comprehended (Zhang et al. 2015), and current techniques often produce imprecise outcomes (Guo et al. 2014; Huang et al. 2014). Hence, this influences the creation of models that forecast urban pollution and alleviate its consequences and effects on society.

2. Deep learning

Thanks to advancements in graphics processing units (GPUs) (HajiRassouliha et al. 2018; Sun et al. 2019), deep learning neural networks (Szegedy et al. 2015; LeCun et al. 2015) have shown exceptional abilities in tasks such as image classification (Krizhevsky et al. 2017; Schofield et al. 2019), generation (Goodfellow et al. 2014), and transformation (Zhu et al. 2017). These technological strides have enabled the application of deep learning to very specialized and technical areas within atmospheric science, thereby improving our capacity to monitor and forecast air quality and comprehend the effects of aerosols on health and the environment. The fusion of deep learning models with conventional methods of atmospheric data collection is leading to the development of more advanced analytical and forecasting tools. Deep learning has revolutionized atmospheric science by providing advanced methods for analyzing complex data and, through the use of convolutional neural networks (CNNs) and long short-term memory (LSTM) networks, offers a sophisticated approach to modeling and understanding the complexities of atmospheric science. These neural networks provide the tools necessary to interpret the vast and varied data involved in this field, leading to improved predictions and a deeper understanding of atmospheric phenomena (Grant-Jacob and Mills 2022).

For localized monitoring, laser-induced spectroscopy is used for particulate matter identification in the Rapid-E automatic particle detector, which collects data from bioaerosols such as pollen and spores (Daunys et al. 2021). Deep learning was incorporated into the Rapid-E for real-time monitoring and automatic airborne classification of pollen using a CNN (Tešendić et al. 2020). CNNs have also been used for identifying PM2.5 sources from wood burning and diesel exhaust using laser scattering (Grant-Jacob et al. 2018) and using fluorescence spectroscopy (Rutherford et al. 2020). On a larger spatial scale, however, deep learning has also been used to determine PM2.5 and PM10 concentrations using MODIS satellite images, with an LSTM-based neural network trained on ground scenes imaged by MODIS (Imani 2021). A method to estimate real-time pollution levels using an image-based deep learning model to approximate air pollution from cityscape photographs has also been demonstrated (Kow et al. 2022). Another broader-coverage technique includes using deep learning for multiwavelength light detection and ranging (lidar) to classify aerosol type (del Águila et al. 2025).

Since urban particulate matter exhibits a diverse range of morphologies and size scales with features below the resolution limit of an optical microscope, electron microscopy is often used to achieve a better understanding of the structure and agglomeration of such particles. The ability to image such particles allows visual insight into the variety of sizes and shapes present in airborne PM, and potential insight into how particulates agglomerate. Owing to the information contained in such images, and owing to a neural network's ability to extract features from such data, such images are valuable for advancing the understanding of airborne particulate matter through deep learning techniques.

Importantly, challenges remain in capturing the temporal evolution of aerosols, particularly the transition from freshly emitted to older particles. This transformation can significantly alter aerosol properties such as size, composition, hygroscopicity, and optical characteristics (Li et al. 2024; Pöschl 2005). Incorporating temporal dynamics into deep learning models is therefore essential for accurately characterizing aerosol behavior across different atmospheric lifetimes.

3. Latent space

In recent years, latent space has emerged as a critical concept in deep learning, particularly in generative models such as generative adversarial networks (GANs) (Isola et al. 2017) and variational autoencoders (VAEs) (Pinheiro Cinelli et al. 2021; Pitsiorlas et al. 2024). Fundamentally, latent space is a lower-dimensional representation of high-dimensional data, achieved by encoding essential features and inherent data structures. This dimensionality reduction is rooted in manifold learning, where it is assumed that data points lie on a smooth, low-dimensional manifold embedded within a higher-dimensional space. In essence, a latent space is an abstract, multidimensional arena where significant internal data representations are encoded. In GANs, the generator model uses points from the latent space to create new instances of data, such as images. Latent spaces, employed in style-based neural networks, possess the ability to generate realistic images of a wide variety of animals and objects, including specific examples like pollen grains. An example of a style-based neural network is StyleGAN (Karras et al. 2019), which stands for style-based generative adversarial network, that enables the production of synthetic images that resemble real-life photographs. Its distinctive structure allows for the unsupervised differentiation of attributes and the stochastic variation in the images it produces. This characteristic facilitates a realistic transition from, for example, one facial image to another, and even from images of one *taxa* of pollen grain to another (Grant-Jacob et al. 2022). The latent W-space is a multidimensional domain that enables the precise spatial representation of data similar to the external space of the neural network, which is the training data. This space also supports comprehensible trajectories within the latent space itself (Voynov and Babenko 2020).

Images can essentially be input into the latent space of a style-based neural network via projection and manipulated using vector arithmetic, offering an alternative to manipulating synthetic images alone. The initial step involves projecting the image into the neural network's latent space by identifying a point in this space that, when processed through the generator, yields an image as similar as possible to the input image. This is typically achieved using optimization techniques with the goal of minimizing the discrepancy between the generated image and the input image. Once a corresponding point in the latent space for the image has been identified, it can be manipulated using vector arithmetic. For instance, latent space vectors associated with specific features (such as spikes on a pollen grain) can be added or subtracted to introduce or remove these features from generated images. These vectors can be identified either by training a separate model to predict these attributes from the latent vectors or by manually gathering examples of images with and without the attribute and calculating the average difference in their latent vectors. After the latent vector has been manipulated, it can be processed through the generator to create a new image that mirrors the modifications made in the latent space.

The StyleGAN network, for example, employs a nonlinear mapping network to transform a random vector into an intermediate latent W-space vector. The components of this vector are correlated with different visual features in the generated image, facilitating smooth transitions between various generated images. For example, the mapping network converts a 1×512 random vector (sampled from a normal distribution with mean zero and standard deviation of one) into a 1×512 latent

W-space vector, which the generation network then transforms into a 512 × 512-pixel resolution image. Therefore, inputs to the generative neural network are supplied in the form of W-space seeds, which are used to generate 512 × 512-pixel images. The process of interpolation between different W-space seeds is accomplished by determining the W-space vector from W-space seed 1 to W-space seed 2 and adding fractions of this vector to the coordinate of W-space seed 1. Given that W-space seeds are random vector coordinates in a 512-dimensional W-space, the interpolation from one W-space seed to another is unique and can be mathematically represented as the position of W-space seed 1 plus a fraction of a vector from W-space seed 1 to W-space seed 2 (computed as W-space seed 2 minus W-space seed 1). Consequently, by averaging numerous W-space vectors from generated images of a specific type of pollen to another (for instance, small to large pollen), a W-space vector for each respective transformation can be identified.

Recent advancements have refined these techniques; for example, in methods that discover interpretable directions within latent space, such as those described by Voynov and Babenko (2020), enable the targeted manipulation of specific data attributes (e.g., adjusting the size or morphology of particle images) without altering unrelated features. This precision is particularly advantageous when modeling complex phenomena like airborne particulate matter, where subtle variations can have significant implications for both health and environmental studies.

The latent space approach has several advantages; for example, by reducing complex atmospheric data into a more manageable representation, it enhances learning and pattern recognition while revealing underlying structures that might be hidden in the original high-dimensional data. However, projecting data into latent space can lead to the loss of detailed information, and the interpretability of latent features can vary depending on the model architecture and training data. Additionally, these models can be sensitive to the quality and representativeness of the training dataset, which is crucial when applying them to real-world atmospheric data.

Nevertheless, compared with traditional dimensionality reduction and feature extraction techniques such as principal component analysis (PCA) (Jolliffe and Cadima 2016), *t*-distributed stochastic neighbor embedding (*t*-SNE) (Van Der Maaten and Hinton 2008), and shallow CNNs (Zeiler and Fergus 2014), latent space models offer several distinctive advantages for analyzing high-dimensional aerosol data. These models can provide richer, more flexible representations and support advanced manipulation and interpretation of aerosol features in both space and time as follows:

- Nonlinear representation: Latent space models can capture complex, curved manifolds that could more accurately reflect the true structure of aerosol populations, including morphological evolution and interparticle interactions. In contrast, linear techniques such as PCA and geometry-preserving methods such as *t*-SNE often fail to preserve these nonlinear dependencies, especially over time and across spatial gradients, and can distort intrinsic relationships in the data.
- Bidirectional encoding and generation: PCA, *t*-SNE, and conventional CNNs reduce data to low-dimensional spaces but offer no reliable inverse mapping, whereas latent space models such as VAEs (Kingma and Welling 2013) and GANs (Karras et al. 2019) support both encoding and decoding. This could allow aerosol images to be embedded into a latent representation and reconstructed or simulated from that space, making it possible to generate controlled variations in morphology.
- Interpretable latent dimensions: While PCA components are often abstract, and shallow CNN feature maps are difficult to interpret, latent variable models can expose semantically meaningful directions. These directions could correspond to measurable aerosol attributes such as particulate size, shape, or agglomeration state and could be manipulated algebraically to explore structure–property or space–time relationships (Voynov and Babenko 2020). For example, particle dynamics influenced by atmospheric conditions (e.g., humidity and turbulence) can be disentangled and studied as trajectories through a latent space.

This combination of nonlinear modeling, generative synthesis, and interpretability makes latent space techniques especially well suited for developing data-driven models of aerosol agglomeration and transport that capture both morphological complexity and the influence of geophysical processes.

4. Future work

The ability to interpolate between images in latent W-space could potentially facilitate the investigation of transformations from one type of particulate matter to another. Given that a neural network groups objects (in this case, particles) based on their visual appearance in latent W-space, the process of interpolation and extrapolation across latent W-space could be analogous to particle agglomeration, provided a path from smaller to larger particles is identified. By employing a CNN to classify the types of agglomerated particles, vectors could enable the addition of specific types of particles to others, thereby facilitating a realistic construction and understanding of particle agglomeration.

Since such agglomeration is in more than two dimensions, 3D imaging of the particulate matter would be beneficial in creating a neural-network-based model that could describe airborne particulate matter agglomeration. Hence, while original style-based neural networks work with 2D images, there have been extensions to work with 3D image arrays. For example, 3D-StyleGAN is a variant that has been developed for generative modeling of three-dimensional full brain magnetic resonance images (Sungmin et al. 2021). The neural network also investigated the controllability and interpretability via style vectors that include the latent space projection and reconstruction of unseen real images and style mixing. Another approach, called Dual Mapping of 2D StyleGAN for 3D-Aware Image Generation, devised a dual-mapping framework to make the generated images of pretrained 2D StyleGAN consistent in 3D space (Chen et al. 2024).

To combine a micro model, i.e., particle agglomeration, and a macro model of atmospheric fluctuations, aerosol transport, and atmospheric effects of air pollution, it could be worth exploring using latent spaces within latent space, such that a micro model exists within a macro model. The structure of the latent space can be complex and hierarchical, allowing for nested latent spaces where one latent space can effectively act as an input for another. This, therefore, could be used to capture more intricate distributions or to model data at different levels of abstraction. For example, in a GAN, a primary latent space could capture high-level features and a secondary latent space could capture more detailed features within the context provided by the primary space. It is possible to envisage a Transformer (Vaswani et al. 2017) type particulate matter latent space that includes not just spatial dimensions, but also a temporal dimension. This latent space could serve as an all-encompassing modeling domain for understanding and mapping particles and their agglomeration in space and time (see Fig. 1 for concept). Unlike LSTMs, Transformers have the advantage of handling long-range dependencies more effectively owing to their self-attention mechanism. This mechanism allows them to focus on different parts of the input sequence when producing an output, thereby making them more flexible and powerful for many tasks. Consequently, Transformers could provide a more effective way to model and understand the distribution and agglomeration of particles in both space and time.

While the hierarchical structure of latent spaces, such as nesting microscale agglomeration models within macroscale atmospheric models, offers a powerful framework for representing particulate matter dynamics, it is important to acknowledge the limitations of Transformer models (Wang et al. 2024a). Although Transformers can model long-range dependencies through self-attention mechanisms, they remain computationally demanding, requiring extensive training data, significant memory resources, and prolonged training times (Fournier et al. 2023). This, therefore, poses a challenge in environmental applications, where high-resolution, time-resolved data are often scarce or unevenly distributed across atmospheric conditions and regions. As such, the development of more comprehensive, multimodal datasets (e.g., combining microscopy, spectroscopy, and satellite data) is essential to fully leverage the potential of Transformer-based models in this field.

To obtain the vast amounts of data that would need to be collected, automation of particle imaging would likely to be necessitated, with relevant metadata such as time stamps and geographic coordinates, as well as consistent imaging protocols would need to be employed. For example, in the original StyleGAN paper, around 20 000 images of faces were used to train the neural network. While many images would be required, combined efforts from multiple sources could be achieved, and a powerful dynamic atmospheric particulate matter model could be developed.

Although LIBS will be limited by its cost and sparse spatial coverage, it would deliver high-resolution spectral data for individual particles. Future work could examine how latent space models might harness these rich, localized datasets by learning transferable representations that align LIBS measurements with broader-scale observations, such as satellite imagery or

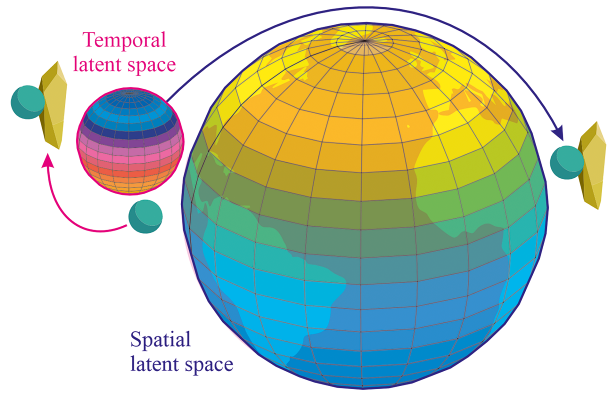

FIG. 1. Concept of using latent space to transform images of urban particles over time and space.

low-cost sensor networks. By capturing latent relationships between microscale particle composition and macroscale atmospheric patterns, this approach would bridge detailed local insights with wide-area monitoring. Rather than deploying LIBS extensively, the technique would use it as a reference modality, enabling models to generalize across spatial scales. Such integration could enhance the ability to infer fine-grained aerosol properties in regions where only coarse data are available, paving the way for more scalable, multiresolution air quality models.

To further advance the application of latent space techniques in atmospheric science, future research could explore several key directions:

- Broader context of aerosol formation: Although aerosol formation mechanisms remain complex, latent space models could help illuminate hidden structures in controlled experiments. By training on time-resolved measurements such as evolving size distributions or spectral absorbance profiles collected under systematically varied precursor gas concentrations, temperature, and humidity, a model's latent variables could trace trajectories corresponding to distinct aerosol growth and transformation regimes, including nucleation, condensation, coagulation, and chemical reaction. While this approach does not replace detailed chemical kinetics, it could uncover empirical patterns in how precursor transformations manifest in observable particle properties, thereby guiding targeted mechanistic studies and improving our ability to interpret laboratory-derived formation pathways.
- Differentiating primary and secondary aerosols: Differentiating between primary and secondary aerosols remains a significant challenge, as both newly emitted particles and those formed via gas-to-particle conversion can appear rapidly and often exhibit similar chemical compositions (Huang et al. 2024) or morphologies (Wang et al. 2024b). A potential way forward could be to train latent-space models on labeled datasets that combine high-resolution imaging features with contextual variables, such as temporal emission profiles, precursor gas concentrations, or chemical speciation proxies. In this framework, the model could learn subtle, multidimensional

patterns that distinguish newly emitted primary aerosols from secondary ones, enabling quantification of each type's contribution to airborne particulate matter even when their visual signatures converge.

- Hierarchical and nested latent representations: Future models should integrate multiple layers of latent representations to capture both fine-scale particle interactions and broad atmospheric dynamics, providing a more comprehensive depiction of air pollution processes through this multitiered approach.
- Integration with cutting-edge architectures: Incorporating Transformer models could significantly enhance the modeling of temporal sequences in atmospheric data, as their self-attention mechanisms allow for more robust tracking of long-range dependencies, which is vital for understanding the evolution of airborne particulate matter over time.
- Multimodal data integration: Latent-space models could offer a way to unify atmospheric data sources by embedding satellite spectral imagery, ground-based sensor time series, and simulation outputs in a shared lower-dimensional space that retains the most informative features from each data type. For example, satellite measurements reveal broad regional aerosol distributions over time and space, while in situ sensors and laboratory instruments deliver precise, time-resolved local observations. By training a single variational autoencoder on both data regimes, the model could discover latent factors that represent common patterns such as composition, aggregation state, and emission source. This unified representation could enable the inference of detailed ground-level particle properties in regions lacking sensors and support early detection of anomalous aerosol events that deviate from expected spatiotemporal trends.
- Systematic evaluation of strengths and limitations: It will be crucial to perform a balanced analysis of latent space methods, acknowledging that while these approaches offer significant computational and analytical advantages, challenges related to data quality, model interpretability, and the risk of overfitting must be addressed through thorough validation and interdisciplinary collaboration.

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REFERENCES

Akinyoola, J. A., A. Oluleye, and I. E. Gbode, 2024: A review of atmospheric aerosol impacts on regional extreme weather and climate events. *Aerosol Sci. Eng.*, **8**, 249–274, https://doi.org/10.1007/s41810-024-00223-x.

Al-Neaimi, Y., J. Gomes, and O. L. Lloyd, 2001: Respiratory illnesses and ventilatory function among workers at a cement factory in a rapidly developing country. *Occup. Med.*, **51**, 367–373, https://doi.org/10.1093/occmed/51.6.367.

Bond, T. C., and Coauthors, 2013: Bounding the role of black carbon in the climate system: A scientific assessment. *J. Geophys. Res. Atmos.*, **118**, 5380–5552, https://doi.org/10.1002/jgrd.50171.

Bozlaker, A., J. M. Prospero, M. P. Fraser, and S. Chellam, 2013: Quantifying the contribution of long-range Saharan dust transport on particulate matter concentrations in Houston, Texas, using detailed elemental analysis. *Environ. Sci. Technol.*, **47**, 10 179–10 187, https://doi.org/10.1021/es4015663.

Cadle, S. H., and Coauthors, 1999: Composition of light-duty motor vehicle exhaust particulate matter in the Denver, Colorado area. *Environ. Sci. Technol.*, **33**, 2328–2339, https://doi.org/10.1021/es9810843.

Calderón-Garcidueñas, L., and Coauthors, 2019: Combustion- and friction-derived magnetic air pollution nanoparticles in human hearts. *Environ. Res.*, **176**, 108567, https://doi.org/10.1016/j.envres.2019.108567.

Chakraborty, R., J. Heydon, M. Mayfield, and L. Mihaylova, 2020: Indoor air pollution from residential stoves: Examining the flooding of particulate matter into homes during real-world use. *Atmosphere*, **11**, 1326, https://doi.org/10.3390/atmos11121326.

Chen, Z., H. Zhao, C. Wang, B. Yuan, and X. Li, 2024: Dual mapping of 2D StyleGAN for 3D-aware image generation and manipulation (student abstract). *Proc. AAAI Conf. Artif. Intell.*, **38**, 23 458–23 459, https://doi.org/10.1609/aaai.v38i21.30428.

Dacunto, P. J., K.-C. Cheng, V. Acevedo-Bolton, R.-T. Jiang, N. E. Klepeis, J. L. Repace, W. R. Ott, and L. M. Hildemann, 2013: Real-time particle monitor calibration factors and $PM_{2.5}$ emission factors for multiple indoor sources. *Environ. Sci. Process. Impacts*, **15**, 1511–1519, https://doi.org/10.1039/c3em00209h.

Daunys, G., L. Šukienė, L. Vaitkevičius, G. Valiulis, M. Sofiev, and I. Šaulienė, 2021: Clustering approach for the analysis of the fluorescent bioaerosol collected by an automatic detector. *PLOS ONE*, **16**, e0247284, https://doi.org/10.1371/journal.pone.0247284.

del Águila, A., P. Ortiz-Amezcua, S. Tabik, J. A. Bravo-Aranda, S. Fernández-Carvelo, and L. Alados-Arboledas, 2025: Aerosol type classification with machine learning techniques applied to multiwavelength lidar data from EARLINET, *EGUsphere*, https://doi.org/10.5194/egusphere-2025-269.

Doiron, D., K. de Hoogh, N. Probst-Hensch, I. Fortier, Y. Cai, S. De Matteis, and A. L. Hansell, 2019: Air pollution, lung function and COPD: Results from the population-based UK Biobank study. *Eur. Respir. J.*, **54**, 1802140, https://doi.org/10.1183/13993003.02140-2018.

Du, Y., X. Xu, M. Chu, Y. Guo, and J. Wang, 2016: Air particulate matter and cardiovascular disease: The epidemiological, biomedical and clinical evidence. *J. Thorac. Dis.*, **8**, E8–E19, https://doi.org/10.3978/j.issn.2072-1439.2015.11.37.

Fournier, Q., G. M. Caron, and D. Aloise, 2023: A practical survey on faster and lighter transformers. *ACM Comput. Surv.*, **55**, 1–40, https://doi.org/10.1145/3586074.

Gallou, G., J. B. Sirven, C. Dutouquet, O. Le Bihan, and E. Frejafon, 2011: Aerosols analysis by LIBS for monitoring of air pollution by industrial sources. *Aerosol Sci. Technol.*, **45**, 918–926, https://doi.org/10.1080/02786826.2011.566899.

Goodfellow, I., J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, and Y. Bengio, 2014: Generative adversarial nets. *NIPS'14: Proc. 28th Int. Conf. on Neural Information Processing Systems – Vol. 2*, Montreal, Quebec, Canada, MIT Press, 2672–2680, https://dl.acm.org/doi/10.5555/2969033.2969125.

Grant-Jacob, J. A., and B. Mills, 2022: Deep learning in airborne particulate matter sensing: A review. *J. Phys. Commun.*, **6**, 122001, https://doi.org/10.1088/2399-6528/aca45e.

——, B. S. Mackay, J. A. G. Baker, D. J. Heath, Y. Xie, M. Loxham, R. W. Eason, and B. Mills, 2018: Real-time particle pollution sensing using machine learning. *Opt. Express*, **26**, 27 237–27 246, https://doi.org/10.1364/OE.26.027237.

——, M. N. Zervas, and B. Mills, 2022: Morphology exploration of pollen using deep learning latent space. *IOP SciNotes*, **3**, 044602, https://doi.org/10.1088/2633-1357/acadb9.

Guarnieri, M., and J. R. Balmes, 2014: Outdoor air pollution and asthma. *Lancet*, **383**, 1581–1592, https://doi.org/10.1016/S0140-6736(14)60617-6.

Guo, S., and Coauthors, 2014: Elucidating severe urban haze formation in China. *Proc. Natl. Acad. Sci. USA*, **111**, 17 373–17 378, https://doi.org/10.1073/pnas.1419604111.

HajiRassouliha, A., A. J. Taberner, M. P. Nash, and P. M. F. Nielsen, 2018: Suitability of recent hardware accelerators (DSPs, FPGAs, and GPUs) for computer vision and image processing algorithms. *Signal Process Image Commun.*, **68**, 101–119, https://doi.org/10.1016/j.image.2018.07.007.

Heredia Rivera, B., and M. Gerardo Rodriguez, 2016: Characterization of airborne particles collected from car engine air filters using SEM and EDX techniques. *Int. J. Environ. Res. Public Health*, **13**, 985, https://doi.org/10.3390/ijerph13100985.

Holgate, S. T., 2017: 'Every breath we take: The lifelong impact of air pollution' - A call for action. *Clin. Med.*, **17**, 8–12, https://doi.org/10.7861/clinmedicine.17-1-8.

Huang, L., and Coauthors, 2024: An improved framework for efficiently modeling organic aerosol (OA) considering primary OA evaporation and secondary OA formation from VOCs, IVOCs, and SVOCs. *Environ. Sci. Atmos.*, **4**, 1064–1078, https://doi.org/10.1039/D4EA00060A.

Huang, R.-J., and Coauthors, 2014: High secondary aerosol contribution to particulate pollution during haze events in China. *Nature*, **514**, 218–222, https://doi.org/10.1038/nature13774.

Imani, M., 2021: Particulate matter ($PM_{2.5}$ and PM_{10}) generation map using MODIS level-1 satellite images and deep neural network. *J. Environ. Manage.*, **281**, 111888, https://doi.org/10.1016/j.jenvman.2020.111888.

Isiugo, K., and Coauthors, 2019: Indoor particulate matter and lung function in children. *Sci. Total Environ.*, **663**, 408–417, https://doi.org/10.1016/j.scitotenv.2019.01.309.

Isola, P., J.-Y. Zhu, T. Zhou, and A. A. Efros, 2017: Image-to-image translation with conditional adversarial networks. *2017 IEEE Conf. on Computer Vision and Pattern Recognition (CVPR)*, Honolulu, HI, Institute of Electrical and Electronics Engineers, 5967–5976, https://doi.org/10.1109/CVPR.2017.632.

Jolliffe, I. T., and J. Cadima, 2016: Principal component analysis: A review and recent developments. *Philos. Trans. Roy. Soc.*, **A374**, 20150202, https://doi.org/10.1098/rsta.2015.0202.

Karras, T., S. Laine, and T. Aila, 2019: A style-based generator architecture for generative adversarial networks. *Proc. IEEE/CVF Conf. on Computer Vision and Pattern Recognition*, Long Beach, CA, Institute of Electrical and Electronics Engineers, 4401–4410, https://doi.org/10.1109/CVPR.2019.00453.

Kelly, F. J., and J. C. Fussell, 2012: Size, source and chemical composition as determinants of toxicity attributable to ambient particulate matter. *Atmos. Environ.*, **60**, 504–526, https://doi.org/10.1016/j.atmosenv.2012.06.039.

Khanna, S. S., and A. S. Gharpure, 2012: Correlation of increased sinusitis and urban air pollution. *Ind. J. Sci. Res. Tech.*, **1**, 14–17.

Kindratenko, V. V., P. J. M. Van Espen, B. A. Treiger, and R. E. Van Grieken, 1994: Fractal dimensional classification of aerosol particles by computer-controlled scanning electron microscopy. *Environ. Sci. Technol.*, **28**, 2197–2202, https://doi.org/10.1021/es00061a031.

Kingma, D. P., and M. Welling, 2013: Auto-encoding variational Bayes. arXiv, 1312.6114v11, https://doi.org/10.48550/arXiv.1312.6114.

Kow, P.-Y., I.-W. Hsia, L.-C. Chang, and F.-J. Chang, 2022: Real-time image-based air quality estimation by deep learning neural networks. *J. Environ. Manage.*, **307**, 114560, https://doi.org/10.1016/j.jenvman.2022.114560.

Krittanawong, C., Y. K. Qadeer, R. B. Hayes, Z. Wang, G. D. Thurston, S. Virani, and C. J. Lavie, 2023: $PM_{2.5}$ and cardiovascular diseases: State-of-the-art review. *Int. J. Cardiol. Cardiovasc. Risk Prev.*, **19**, 200217, https://doi.org/10.1016/j.ijcrp.2023.200217.

Krizhevsky, A., I. Sutskever, and G. E. Hinton, 2017: ImageNet classification with deep convolutional neural networks. *Commun. ACM*, **60**, 84–90, https://doi.org/10.1145/3065386.

Langmann, B., 2014: On the role of climate forcing by volcanic sulphate and volcanic ash. *Adv. Meteor.*, **2014**, 340123, https://doi.org/10.1155/2014/340123.

LeCun, Y., Y. Bengio, and G. Hinton, 2015: Deep learning. *Nature*, **521**, 436–444, https://doi.org/10.1038/nature14539.

Lelieveld, J., A. Pozzer, U. Pöschl, M. Fnais, A. Haines, and T. Münzel, 2020: Loss of life expectancy from air pollution compared to other risk factors: A worldwide perspective. *Cardiovasc. Res.*, **116**, 1910–1917, https://doi.org/10.1093/cvr/cvaa025.

Levetin, E., C. A. Rogers, and S. A. Hall, 2000: Comparison of pollen sampling with a Burkard spore trap and a Tauber trap in a warm temperate climate. *Grana*, **39**, 294–302, https://doi.org/10.1080/00173130052504333.

Li, W., and Coauthors, 2024: Microphysical properties of atmospheric soot and organic particles: Measurements, modeling, and impacts. *npj Climate Atmos. Sci.*, **7**, 65, https://doi.org/10.1038/s41612-024-00610-8.

Li, Z., Q. Wen, and R. Zhang, 2017: Sources, health effects and control strategies of indoor fine particulate matter ($PM_{2.5}$): A review. *Sci. Total Environ.*, **586**, 610–622, https://doi.org/10.1016/j.scitotenv.2017.02.029.

Ličbinský, R., A. Frýbort, J. Huzlík, V. Adamec, K. Effenberger, P. Mikuška, M. Vojtěšek, and K. Křůmal, 2010: Usage of scanning electron microscopy for particulate matter sources identification. *Trans. Transp. Sci.*, **3**, 137–144, https://doi.org/10.2478/v10158-010-0019-8.

Maenhaut, W., R. Vermeylen, M. Claeys, J. Vercauteren, and E. Roekens, 2016: Sources of the PM10 aerosol in Flanders, Belgium, and re-assessment of the contribution from wood burning. *Sci. Total Environ.*, **562**, 550–560, https://doi.org/10.1016/j.scitotenv.2016.04.074.

Maher, B. A., and Coauthors, 2016: Magnetite pollution nanoparticles in the human brain. *Proc. Natl. Acad. Sci. USA*, **113**, 10 797–10 801, https://doi.org/10.1073/pnas.1605941113.

Mazzei, F., A. D'Alessandro, F. Lucarelli, S. Nava, P. Prati, G. Valli, and R. Vecchi, 2008: Characterization of particulate matter sources in an urban environment. *Sci. Total Environ.*, **401**, 81–89, https://doi.org/10.1016/j.scitotenv.2008.03.008.

McInnes, R. N., D. Hemming, P. Burgess, D. Lyndsay, N. J. Osborne, C. A. Skjøth, S. Thomas, and S. Vardoulakis, 2017: Mapping allergenic pollen vegetation in UK to study environmental exposure and human health. *Sci. Total Environ.*, **599–600**, 483–499, https://doi.org/10.1016/j.scitotenv.2017.04.136.

Meng, X., Y. Yu, and P. Ginoux, 2025: Rise in dust emissions from burned landscapes primarily driven by small fires. *Nat. Geosci.*, **18**, 586–592, https://doi.org/10.1038/s41561-025-01730-3.

Miller-Schulze, J. P., and Coauthors, 2015: Seasonal contribution of mineral dust and other major components to particulate matter at two remote sites in Central Asia. *Atmos. Environ.*, **119**, 11–20, https://doi.org/10.1016/j.atmosenv.2015.07.011.

Ni, R., H. Su, R. T. Burnett, Y. Guo, and Y. Cheng, 2024: Long-term exposure to $PM_{2.5}$ has significant adverse effects on childhood and adult asthma: A global meta-analysis and health impact assessment. *One Earth*, **7**, 1953–1969, https://doi.org/10.1016/j.oneear.2024.09.022.

Nriagu, J. O., 1989: A global assessment of natural sources of atmospheric trace metals. *Nature*, **338**, 47–49, https://doi.org/10.1038/338047a0.

Orellano, P., M.-I. Kasdagli, R. Pérez Velasco, and E. Samoli, 2024: Long-term exposure to particulate matter and mortality: An update of the WHO global air quality guidelines systematic review and meta-analysis. *Int. J. Public Health*, **69**, 1607683, https://doi.org/10.3389/ijph.2024.1607683.

Park, J., and Coauthors, 2017: Spatial–Temporal dispersion of aerosolized nanoparticles during the use of consumer spray products and estimates of inhalation exposure. *Environ. Sci. Technol.*, **51**, 7624–7638, https://doi.org/10.1021/acs.est.7b00211.

Peel, R. G., R. Kennedy, M. Smith, and O. Hertel, 2014: Relative efficiencies of the Burkard 7-day, Rotorod and Burkard personal samplers for Poaceae and Urticaceae pollen under field conditions. *Ann. Agric. Environ. Med.*, **21**, 745–752, https://doi.org/10.5604/12321966.1129927.

Peters, R., N. Ee, J. Peters, A. Booth, I. Mudway, and K. J. Anstey, 2019: Air pollution and dementia: A systematic review. *J. Alzheimers. Dis.*, **70**, S145–S163, https://doi.org/10.3233/JAD-180631.

Pinheiro Cinelli, L., M. Araújo Marins, E. A. Barros da Silva, and S. L. Netto, 2021: Variational autoencoder. *Variational Methods for Machine Learning with Applications to Deep Networks*, Springer, 111–149.

Pitsiorlas, I., A. Tsantalidou, G. Arvanitakis, M. Kountouris, and C. Kontoes, 2024: A latent space metric for enhancing prediction confidence in Earth observation data. *IGARSS 2024 - 2024 IEEE Int. Geoscience and Remote Sensing Symp.*, Athens, Greece, Institute of Electrical and Electronics Engineers, 987–991, https://doi.org/10.1109/IGARSS53475.2024.10641865.

Pöschl, U., 2005: Atmospheric aerosols: Composition, transformation, climate and health effects. *Angew. Chem.*, **44**, 7520–7540, https://doi.org/10.1002/anie.200501122.

Raaschou-Nielsen, O., and Coauthors, 2013: Air pollution and lung cancer incidence in 17 European cohorts: Prospective analyses from the European Study of Cohorts for Air Pollution Effects (ESCAPE). *Lancet. Oncol.*, **14**, 813–822, https://doi.org/10.1016/S1470-2045(13)70279-1.

Raes, F., R. van Dingenen, E. Vignati, J. Wilson, J.-P. Putaud, J. H. Seinfeld, and P. Adams, 2000: Formation and cycling of aerosols in the global troposphere. *Atmos. Environ.*, **34**, 4215–4240, https://doi.org/10.1016/S1352-2310(00)00239-9.

Rutherford, J. W., N. Dawson-Elli, A. M. Manicone, G. V Korshin, I. V Novosselov, E. Seto, and J. D. Posner, 2020: Excitation emission matrix fluorescence spectroscopy for combustion generated particulate matter source identification. *Atmos. Environ.*, **220**, 117065, https://doi.org/10.1016/j.atmosenv.2019.117065.

Schofield, D., A. Nagrani, A. Zisserman, M. Hayashi, T. Matsuzawa, D. Biro, and S. Carvalho, 2019: Chimpanzee face recognition from videos in the wild using deep learning. *Sci. Adv.*, **5**, eaaw0736, https://doi.org/10.1126/sciadv.aaw0736.

Seinfeld, J. H., and S. N. Pandis, 2016: *Atmospheric Chemistry and Physics: From Air Pollution to Climate Change.* John Wiley and Sons, 1152 pp.

Sorensen, C. M., 2001: Light scattering by fractal aggregates: A review. *Aerosol Sci. Technol.*, **35**, 648–687, https://doi.org/10.1080/02786820117868.

Sun, Y., N. B. Agostini, S. Dong, and D. Kaeli, 2019: Summarizing CPU and GPU design trends with product data. arXiv, 1911.11313v2, https://doi.org/10.48550/arXiv.1911.11313.

Sungmin, H., R. Marinescu, A. V. Dalca, A. K. Bonkhoff, M. Bretzner, N. S. Rost, and P. Golland, 2021: 3D-StyleGAN: A style-based generative adversarial network for generative modeling of three-dimensional medical images. *Deep Generative Models, and Data Augmentation, Labelling, and Imperfections*, S. Engelhardt et al., Eds., Lecture Notes in Computer Science, Vol. 13003, Springer International Publishing, 24–34.

Szegedy, C., and Coauthors, 2015: Going deeper with convolutions. *Proc. IEEE Conf. on Computer Vision and Pattern Recognition*, Boston, MA, Institute of Electrical and Electronics Engineers, 1–9, https://doi.org/10.1109/CVPR.2015.7298594.

Tešendić, D., D. Boberić Krstićev, P. Matavulj, S. Brdar, M. Panić, V. Minić, and B. Šikoparija, 2020: RealForAll: Real-time system for automatic detection of airborne pollen. *Enterp. Inf. Syst.*, **16**, 1793391, https://doi.org/10.1080/17517575.2020.1793391.

Thaichana, P., and Coauthors, 2025: Association of maternal $PM_{2.5}$ exposure with preterm birth and low birth weight: A large-scale cohort study in Northern Thailand (2016–2022). *Toxics*, **13**, 304, https://doi.org/10.3390/toxics13040304.

Thorpe, A., and R. M. Harrison, 2008: Sources and properties of non-exhaust particulate matter from road traffic: A review. *Sci. Total Environ.*, **400**, 270–282, https://doi.org/10.1016/j.scitotenv.2008.06.007.

Tomasi, C., and A. Lupi, 2017: Coagulation, condensation, dry and wet deposition, and cloud droplet formation in the atmospheric aerosol life cycle. *Atmospheric Aerosols: Life Cycles and Effects on Air Quality and Climate*, C. Tomasi, S. Fuzzi, and A. Kokhanovsky, Eds., Wiley, 115–182.

Van Der Maaten, L., and G. Hinton, 2008: Visualizing data using t-SNE. *J. Mach. Learn. Res.*, **9**, 2579–2605.

Vaswani, A., N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, Ł. Kaiser, and I. Polosukhin, 2017: Attention is all you need. *Proc. 31st Int. Conf. on Neural Information Processing Systems*, Long Beach, CA, Curran Associates Inc., 6000–6010, https://dl.acm.org/doi/10.5555/3295222.3295349.

Vehkamäki, H., and I. Riipinen, 2012: Thermodynamics and kinetics of atmospheric aerosol particle formation and growth. *Chem. Soc. Rev.*, **41**, 5160–5173, https://doi.org/10.1039/c2cs00002d.

Venkataraman, C., G. Habib, A. Eiguren-Fernandez, A. H. Miguel, and S. K. Friedlander, 2005: Residential biofuels in South Asia: Carbonaceous aerosol emissions and climate impacts. *Science*, **307**, 1454–1456, https://doi.org/10.1126/science.1104359.

Voynov, A., and A. Babenko, 2020: Unsupervised discovery of interpretable directions in the GAN latent space. *Proc. 37th Int. Conf. on Machine Learning*, Vienna, Austria, JMLR.org, 9786–9796, https://dl.acm.org/doi/abs/10.5555/3524938.3525845.

Wang, J., D. Li, Y. Ma, L. Tang, J. Xie, Y. Hu, and Y. Tian, 2023: Long-term exposure to ambient air pollutants and increased risk of pneumonia in the UK biobank. *Chest*, **164**, 39–52, https://doi.org/10.1016/j.chest.2023.02.018.

Wang, R., L. Ma, G. He, B. A. Johnson, Z. Yan, M. Chang, and Y. Liang, 2024a: Transformers for remote sensing: A systematic review and analysis. *Sensors*, **24**, 3495, https://doi.org/10.3390/s24113495.

Wang, Y., P. Zhang, J. Li, Y. Liu, Y. Zhang, J. Li, and Z. Han, 2024b: An updated aerosol simulation in the Community Earth System Model (v2.1.3): Dust and marine aerosol emissions and secondary organic aerosol formation. *Geosci. Model Dev.*, **17**, 7995–8021, https://doi.org/10.5194/gmd-17-7995-2024.

World Health Organization, 2006: *Air Quality Guidelines: Global Update 2005: Particulate Matter, Ozone, Nitrogen Dioxide, and Sulfur Dioxide.* World Health Organization, 484 pp.

Xiong, C., and S. K. Friedlander, 2001: Morphological properties of atmospheric aerosol aggregates. *Proc. Natl. Acad. Sci. USA*, **98**, 11 851–11 856, https://doi.org/10.1073/pnas.211376098.

Yao, Q., S.-Q. Li, H.-W. Xu, J.-K. Zhuo, and Q. Song, 2009: Studies on formation and control of combustion particulate matter in China: A review. *Energy*, **34**, 1296–1309, https://doi.org/10.1016/j.energy.2009.03.013.

Zeb, B., K. Alam, A. Sorooshian, T. Blaschke, I. Ahmad, and I. Shahid, 2018: On the morphology and composition of particulate matter in an urban environment. *Aerosol Air Qual. Res.*, **18**, 1431–1447, https://doi.org/10.4209/aaqr.2017.09.0340.

Zeiler, M. D., and R. Fergus, 2014: Visualizing and understanding convolutional networks. *Computer Vision – ECCV 2014*, D. Fleet et al., Eds., Lecture Notes in Computer Science, Vol. 8689, Springer International Publishing, 818–833.

Zhang, R., and Coauthors, 2015: Formation of urban fine particulate matter. *Chem. Rev.*, **115**, 3803–3855, https://doi.org/10.1021/acs.chemrev.5b00067.

——, and Coauthors, 2018: Morphology and property investigation of primary particulate matter particles from different sources. *Nano Res.*, **11**, 3182–3192, https://doi.org/10.1007/s12274-017-1724-y.

Zhu, J.-Y., T. Park, P. Isola, and A. A. Efros, 2017: Unpaired image-to-image translation using cycle-consistent adversarial networks. *2017 IEEE Int. Conf. on Computer Vision (ICCV)*, Venice, Italy, Institute of Electrical and Electronics Engineers, 2242–2251, https://doi.org/10.1109/ICCV.2017.244.

Zuurbier, M., G. Hoek, M. Oldenwening, V. Lenters, K. Meliefste, P. van den Hazel, and B. Brunekreef, 2010: Commuters' exposure to particulate matter air pollution is affected by mode of transport, fuel type, and route. *Environ. Health Perspect.*, **118**, 783–789, https://doi.org/10.1289/ehp.0901622.