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AI AND DATA-DRIVEN MODEL REDUCTION FOR ENVIRONMENTAL FLOWS

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ABSTRACT

Environmental flows, including atmospheric boundary layers, urban flows, and pollutant dispersion, are characterized by strong nonlinearity, turbulence, and multiscale interactions. These challenges are encountered across a wide range of spatial scales and physical settings, from street-level urban environments to regional and global atmospheric flows. Numerical simulations, such as large-eddy simulation (LES) and mesoscale models, provide detailed insights; however, they remain computationally expensive and are often unsuitable for real-time applications and operational forecasting.

Recent advances in artificial intelligence (AI), machine learning, and data-driven modeling have enabled new approaches to accelerate simulations and construct reduced-order models (ROMs) that retain essential physical characteristics. In particular, neural operators, autoencoder-based ROMs, operator inference, and hybrid physics–AI models offer promising frameworks for bridging the gap between high-fidelity simulations and real-time prediction.

This minisymposium aims to bring together researchers working on AI-driven model reduction and data-driven approaches for environmental flows across diverse physical settings and scales, ranging from urban microenvironments to mesoscale and global climate flows. The focus is on developing scalable, physically consistent, and interpretable models that integrate numerical simulations, observational data, and machine learning techniques.

Topics of Interest

- Data-driven reduced-order modeling (POD, autoencoders, neural operators)
- AI-based prediction of wind, temperature, and humidity fields
- Bias correction of numerical weather prediction models
- Physics-informed machine learning
- Data assimilation and sensor integration
- Multi-fidelity and surrogate modeling across scales
- Urban climate and air quality modeling
- Urban heat island analysis and mitigation using data-driven methods

- Pedestrian-level wind and thermal comfort prediction
- Environmental digital twins and real-time forecasting