

Johns Hopkins University

**Center for Environmental
& Applied Fluid Mechanics**

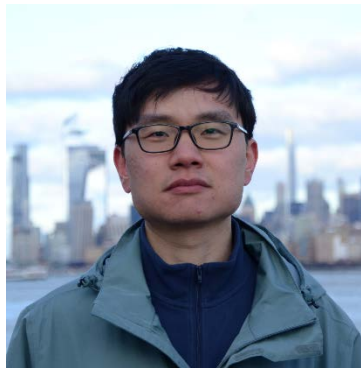
3:00 PM, Friday, October 3, 2025

Gilman Hall 50

Zoom: <https://wse.zoom.us/j/93762992307>

[Link for Fall 2025 recordings](#)

Winner of the 2023 Corrsin-Kovaszny Outstanding Paper Award



Dr. Mengze Wang

Department of Mechanical Engineering
Massachusetts Institute of Technology

***“Bridging Model and Reality: Optimal Prediction of Turbulence through
Assimilating Limited Observations”***

Abstract: Numerical simulations of chaotic and multiscale systems, such as engineering turbulence and global climate, present significant challenges. Even at the highest level of simulation fidelity, due to the assumptions introduced in initial condition, boundary condition, or model parameters, numerical predictions often deviate from experimental measurements or field tests. Data assimilation provides a systematic framework to address these limitations by optimally infusing limited observations into numerical simulations, enabling the full access to all the scales. In this talk, I will first focus on canonical wall-bounded turbulence, where the incompressible Navier-Stokes equations are generally considered a perfect model for describing flow physics. Given limited velocity data, our objective is to construct a Navier-Stokes solution that reproduces these observations and predict the unknown flows. A critical data resolution is identified that ensures an accurate reconstruction of turbulence. Below this critical threshold, the origins of measurements become increasingly ambiguous, and only the flows within the domain of dependence of observations can be accurately decoded. I will then address the more challenging scenario of biased model equations, using climate simulations as an example. A prediction-correction strategy will be presented, where data assimilation is utilized to nudge the simulations towards observations. These aligned simulation-observation pairs are then used to train a machine-learning model that identifies and removes systematic biases. When applied to free-running climate simulations, this framework demonstrates significant improvements in capturing the statistics of rare events.

Hosted by: Prof. Tamer Zaki (MechE)