17th World Congress on Computational Mechanics
10th European Congress on Computational Methods in Applied Sciences and Engineering
WCCM-ECCOMAS2026
July 19-24, 2026, Munich, Germany

GENERTATIVE MODELS FOR INVERSE PROBLEMS, DATA ASSIMILATION AND UNCERTAINTY QUANTIFICATION

TRACK NUMBER 600

ASSAD A. OBERAI*, JIAN-XUN WANG† AND ROGER GHANEM*

* University of Southern California, Los Angeles, CA 90089, USA
aoberai@usc.edu, ghanem@usc.edu

† Cornell University,
Ithaca, USA, 14853
Jw2837@cornell.edu and https://jianxunwang.engineering.cornell.edu/pi-jian-xun-wang/

Keywords: generative models, diffusion and flow matching, inverse problems, data assimilation, uncertainty quantification

ABSTRACT

Generative models such as diffusion models, flow-matching models, stochastic interpolants, and normalizing flows have shown remarkable success in generating realistic images and videos. More recently, these models have been applied to inverse problems and data assimilation tasks in science and engineering. Notable achievements include the discovery of three-dimensional protein structures and the generation of highly accurate weather forecasts. These advances have spurred a surge of interest in applying generative models across a wide range of scientific and engineering domains. In turn, these applications have driven new research directions focused on method development. Key areas of ongoing investigation include: enforcing physical constraints during sample generation; analyzing convergence properties; developing models capable of handling both sparse observations and continuous streaming data; improving efficiency and scalability; and extending these methods to address multiscale and multiphysics problems.

Motivated by these developments, this minisymposium invites submissions focused on the development, extension, and application of state-of-the-art generative models for inverse problems and data assimilation. Topics of interest include, but are not limited to:

- Incorporating physical constraints into generative models
- Analyzing generative models as tools for probabilistic inference
- Extending generative models to settings with limited training data
- Applying generative models for state and parameter inference in dynamical systems
- Evaluating the performance of generative models for probabilistic inference
- Developing novel formulations for faster and more scalable inference