

# Guided Unconditional and Conditional Generative Models for Super-Resolution and Inference of Quasi-Geostrophic Turbulence

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## Key Points:

- We benchmark four diffusion models for sparse super-resolution and inference of forced 2D quasi-geostrophic turbulence in the  $\beta$ -plane
- Conditional diffusion models remain stable, predict correct statistics, and generalize even with sparse and gappy coarse observations
- Guided unconditional models may ineffectively propagate information to unobserved regions when observation operators are sparse and local

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## Abstract

Typically, numerical simulations of Earth systems are coarse, and Earth observations are sparse and gappy. We apply four generative diffusion modeling approaches to super-resolution and inference of forced two-dimensional quasi-geostrophic turbulence on the  $\beta$ -plane from coarse, sparse, and gappy observations. Two guided approaches minimally adapt a pre-trained unconditional model: SDEdit modifies the initial condition, and Diffusion Posterior Sampling (DPS) modifies the reverse diffusion process's score. Two conditional approaches, a vanilla variant and classifier-free guidance, require training with paired high-resolution and observation data. We consider multiple test cases spanning: two regimes, eddy and anisotropic-jet turbulence; two Reynolds numbers,  $10^3$  and  $10^4$ ; and two observation types,  $4\times$  coarse-resolution fields and coarse, sparse and gappy observations. Our comprehensive skill metrics include norms of the reconstructed vorticity fields, turbulence statistical quantities, and quantifications of the super-resolved probabilistic ensembles and their errors. We also study the sensitivity to tuning parameters such as guidance strength. Results show that the generated super-resolution fields of SDEdit are unphysical, while those of DPS are reasonable but with smoothed fine-scale features; however, neither of these lower-cost models propagates observational information effectively to unobserved regions. The two conditional models require re-training, but reconstruct missing fine-scale features, are cycle-consistent with observations, and predict correct turbulence statistics, including the tails. Further, their mean errors are highly correlated with and predictable from their ensemble standard deviations. Results highlight the trade-offs between ease of implementation, fidelity (sharpness), and cycle-consistency of the diffusion models, and offer practical guidance for deployment in geophysical inverse problems.

## Plain Language Summary

Simulating the ocean or the atmosphere at high resolution is expensive because computers solve physics equations on many tiny grid cells. As an approximation, simulations are run with a small number of large grid cells, missing important small-scale physics such as swirling eddies. Even geophysical observations with satellites, balloons, buoys, or robots can be incomplete with large gaps. We explore whether generative diffusion models, a new machine learning technique, can complete the missing details in ways that respect the laws of physics. Using turbulence simulations, we compare four diffusion models. Two *conditional* models require training from scratch to directly learn missing details, demanding more data and computation, while two *guided unconditional* models modify existing diffusion models to complete missing details. We find that conditional models create realistic details that respect turbulence physics. In challenging cases, one of the unconditional models fails, while the other can provide low-cost, reasonable guesses. We show tradeoffs between resource use and realism that users can tune to their needs. Some generative diffusion models can lead to sharper maps of ocean currents, weather, and climate, help merge real observations with simulations, and possibly learn physics from even incomplete, indirect data.

## 1 Introduction

Higher-resolution oceanic and atmospheric modeling for marine, weather, and climate predictions (Kalnay, 2003; Harris & Lin, 2014; E. P. Chassignet & Xu, 2021; Brotzge et al., 2023; Lai et al., 2024) can provide greater accuracy but are computationally expensive. Numerical models are limited not only by their spatio-temporal resolution but also by the processes they represent and the number of variables they simulate (Gupta & Lermusiaux, 2021; Jacobs et al., 2023). For example, simulating the full range of spatio-temporal scales in turbulent flows is computationally intractable; approximations and parameterizations, such as in Large-Eddy Simulations (LES), are thus employed to rep-