

# DiffObs: Generative Diffusion for Global Forecasting of Satellite Observations



NVIDIA®

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## Introduction

Presenting a computationally ambitious, autoregressive generative diffusion model (**DiffObs**) to predict the high-resolution global evolution of daily precipitation from a satellite observational product.

**Question:** can we generate realistic convectively coupled tropical disturbances across daily to multi-week simulations?

**Motivation:** tropical atmospheric variability regulates subseasonal predictability, but **(a)** is challenging to capture realistically in physics-based models and is incompletely understood, and **(b)** most machine learning approaches use complete state information at smaller spatial/temporal scales; GPU advances enable more ambition today.

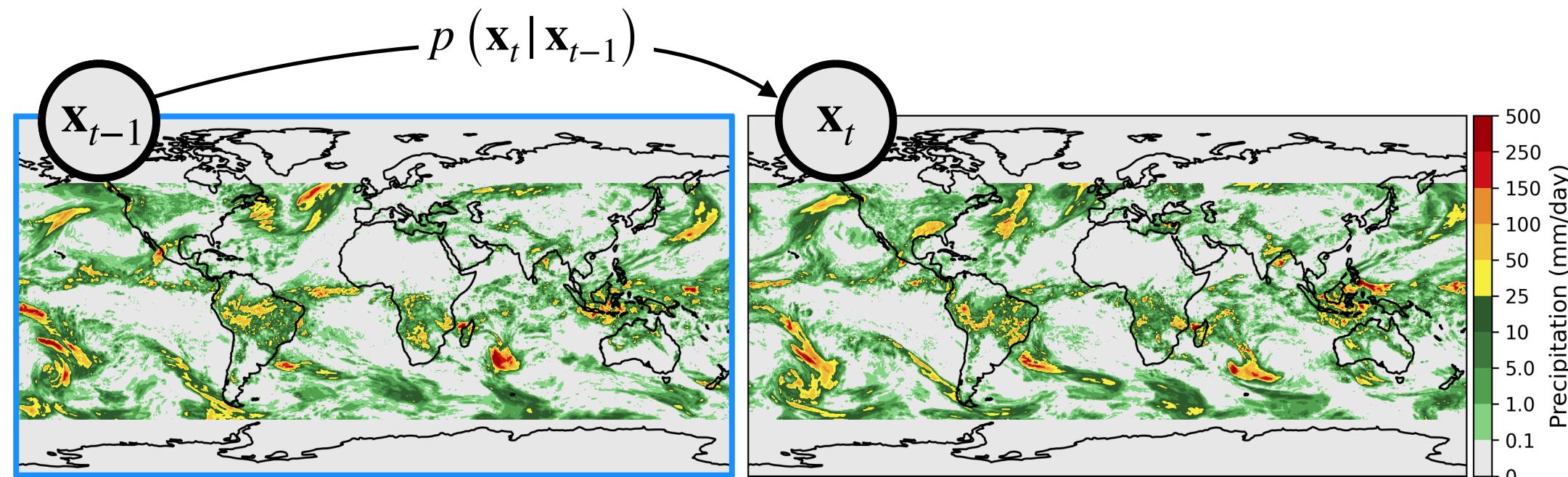


Figure 1: Single step output  $\mathbf{x}_t$  from DiffObs when conditioned on the previous state  $\mathbf{x}_{t-1}$

## Dataset Details

Final precipitation, half hourly Integrated Multi-satellitE Retrievals for Global Perception Measurements (IMERG) L3 Version 06B data (Figure 1).

- **Aggregation:** all half hour samples are daily-accumulated (in mm/d).
- **Spatial Coverage:** grid coarsening from  $0.1^\circ \rightarrow 0.4^\circ$  with cropping in the meridional direction (at poles) between  $56.2^\circ\text{N}$  and  $61.8^\circ\text{S}$ .
- **Temporal Partitioning:** separated by years, with 2000–2016 (6,041) for training and 2017–2022 (1,729) for testing, total samples in parentheses.

## Experimental Results

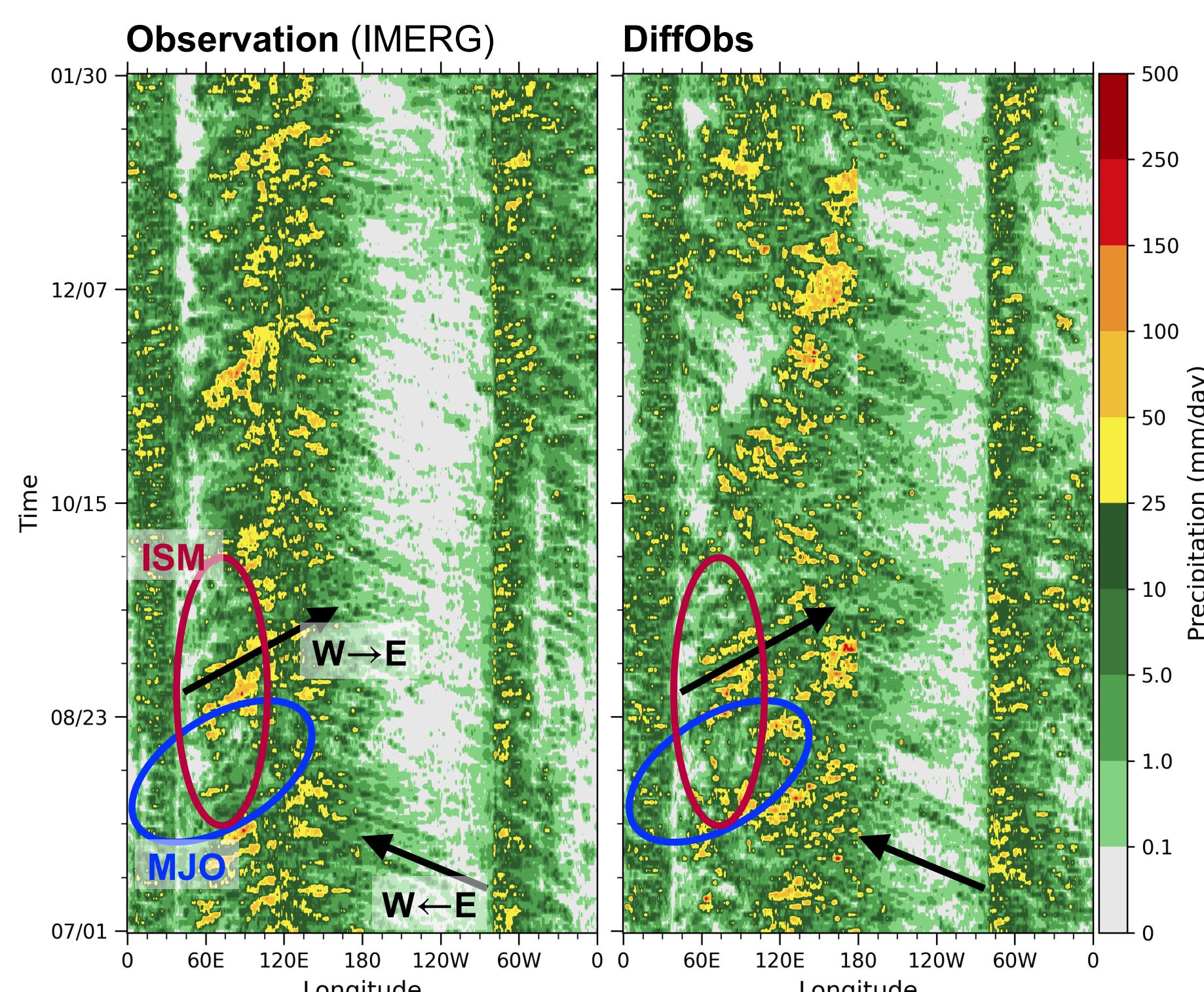


Figure 3: Hovmöller diagrams (between  $5^\circ\text{S}$  and  $5^\circ\text{N}$ ) initialized on July 1, 2020.

**Hovmöller Diagram:** we generate long rollouts from an initial state, averaging the outputs around the equator and stacking temporally to identify patterns.

**Results** → superposition of eastward- and westward-propagating tropical disturbances, modulated by a large-scale envelope of slow, eastward moving variability characteristic of the Madden–Julian oscillation (MJO).

**Additional Features (?)**: secondary model with **(a)** *temporal conditioning* by zonal averaging the cosine of solar zenith angle as a function of the input condition's date and latitudes, and **(b)** *coordinate conditioning* with static spatially bound sin/cos (lon) to counter the network's rotational equivariance.

**Results** → suboptimal performance with inconsistent atmospheric dynamics, including missing landmass influence, tropical wave modes, and directionality.

## Methodology

**Goal:** probabilistically forecast day-ahead precipitation, estimating  $p(\mathbf{x}_t | \mathbf{x}_{t-1})$  without incorporating any additional priors.

**Soln:** train a 13.6M param conditional EDM diffusion model (adapted UNet architecture) on a cluster of  $256 \times 80\text{GB}$  H100 NVIDIA GPUs (32 nodes) using a global batch size of 1,024 for 12.5M total steps.

**Diffusion Details:** consider the following **forward SDE**

$$d\mathbf{x} = \sqrt{2\dot{\sigma}(t)\sigma(t)} d\omega_t \quad t \in [0,1],$$

then the **reverse-time SDE** (Figure 2) is given by

$$d\mathbf{x} = -2\dot{\sigma}(t)\sigma(t) \nabla_{\mathbf{x}} \log p(\mathbf{x}; \sigma(t)) dt + \sqrt{2\dot{\sigma}(t)\sigma(t)} d\bar{\omega}_t.$$

We estimate  $\nabla_{\mathbf{x}} \log p(\mathbf{x}; \sigma) = (D_\theta(\mathbf{x}, \sigma) - \mathbf{x})/\sigma^2$  with a denoising neural network  $D_\theta$  conditioned on  $\mathbf{x}_{t-1}$  (via channel-wise concatenated) by minimizing

$$\min_{\theta} \mathbb{E}_{\mathbf{x}_{t,t-1} \sim p_{\text{data}}} \mathbb{E}_{\sigma \sim p_{\sigma}} \mathbb{E}_{\mathbf{n} \sim \mathcal{N}(\mathbf{0}, \sigma^2 \mathbf{I})} [\lambda(\sigma) \|D_\theta(\mathbf{x}_t + \mathbf{n}, \mathbf{x}_{t-1}; \sigma) - \mathbf{x}_t\|_2^2]$$

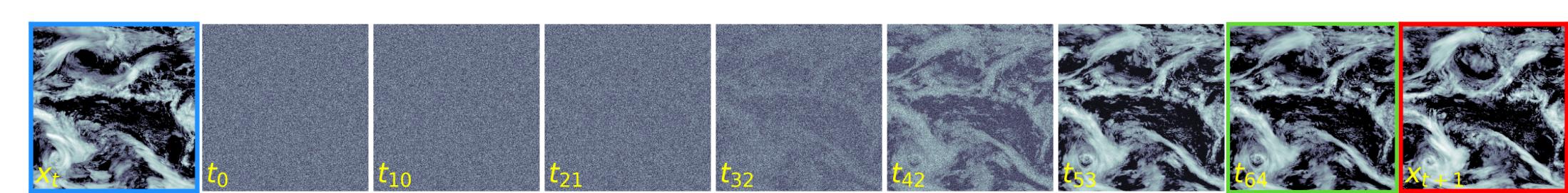


Figure 2: Reverse diffusion with the condition, sampling steps, next step estimate, and target output

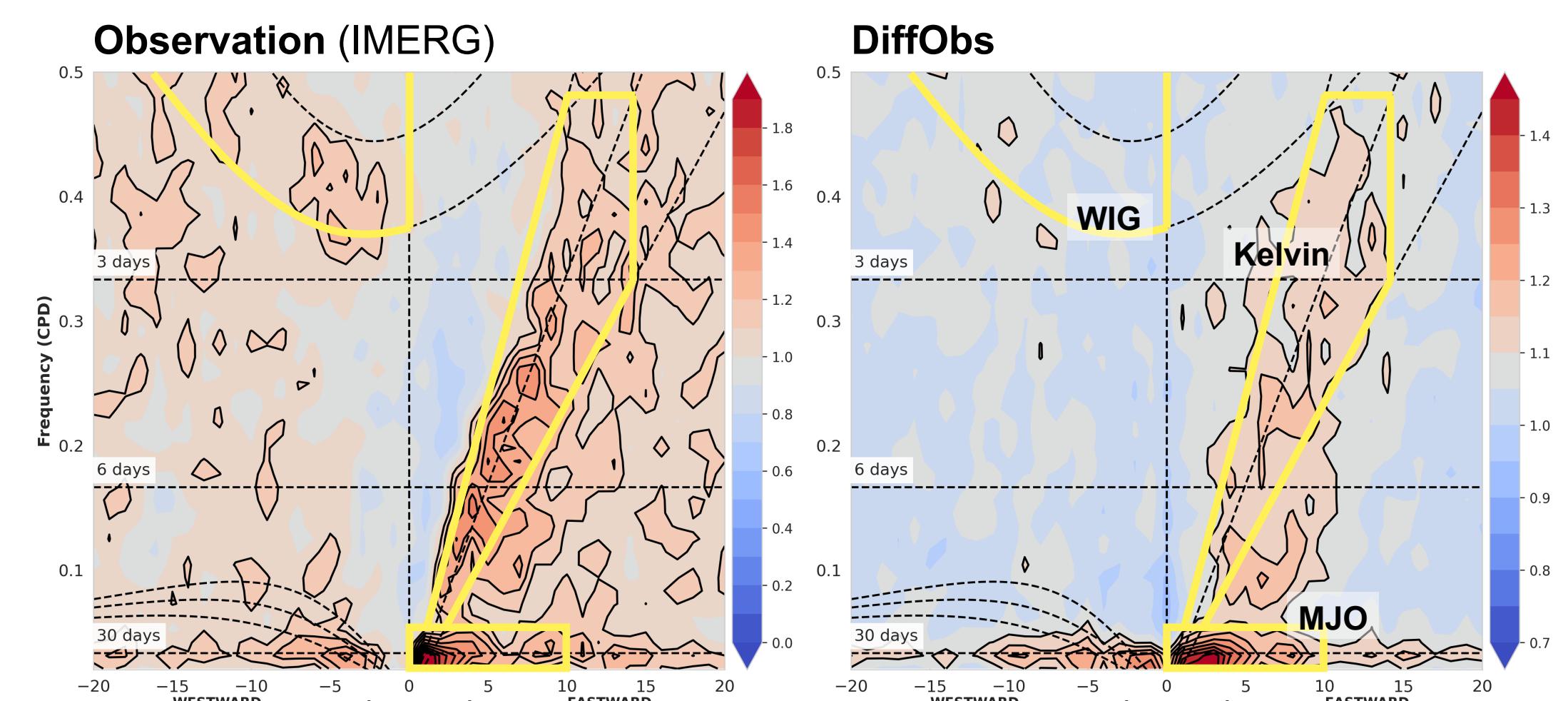


Figure 4: Symmetric / Background Wheeler-Kiladis space-time spectra between  $15^\circ\text{S}$  and  $15^\circ\text{N}$

**Spectral Analysis:** we generate 80 yrs of data on one-day intervals, initially conditioning 1 yr rollouts on Jan 1 for years 2017–2021 and sample with perturbed noise, concatenating the results temporally prior to analysis.

**Results** → discovery of Kelvin wave and strong MJO spectral signals within the signal-to-noise ratio of the equatorially-symmetric component.

## Conclusions

**Overview:** we autoregressively generate multi-month, high-resolution rollouts of univariate observations, showing with domain-specific diagnostics (Hovmöller / Wheeler-Kiladis) stable rollouts and a realistic spectrum of tropical wave modes.

**Takeaways:** global diffusion models trained on sparse observations of the world show promise for applications in subseasonal and climate prediction.

**Predictability (?)**: not our main focus, yet we find the best skill (RMSE / FSS) out to 3- to 5-day lead times when compared to persistence and climatology.

**Future Work:** leverage lower-level products, explicitly model the temporal distributions, and compare to numerical weather prediction and reanalysis.



← arXiv (2404.06517) paper

<sup>2</sup> work done during an internship at NVIDIA  
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