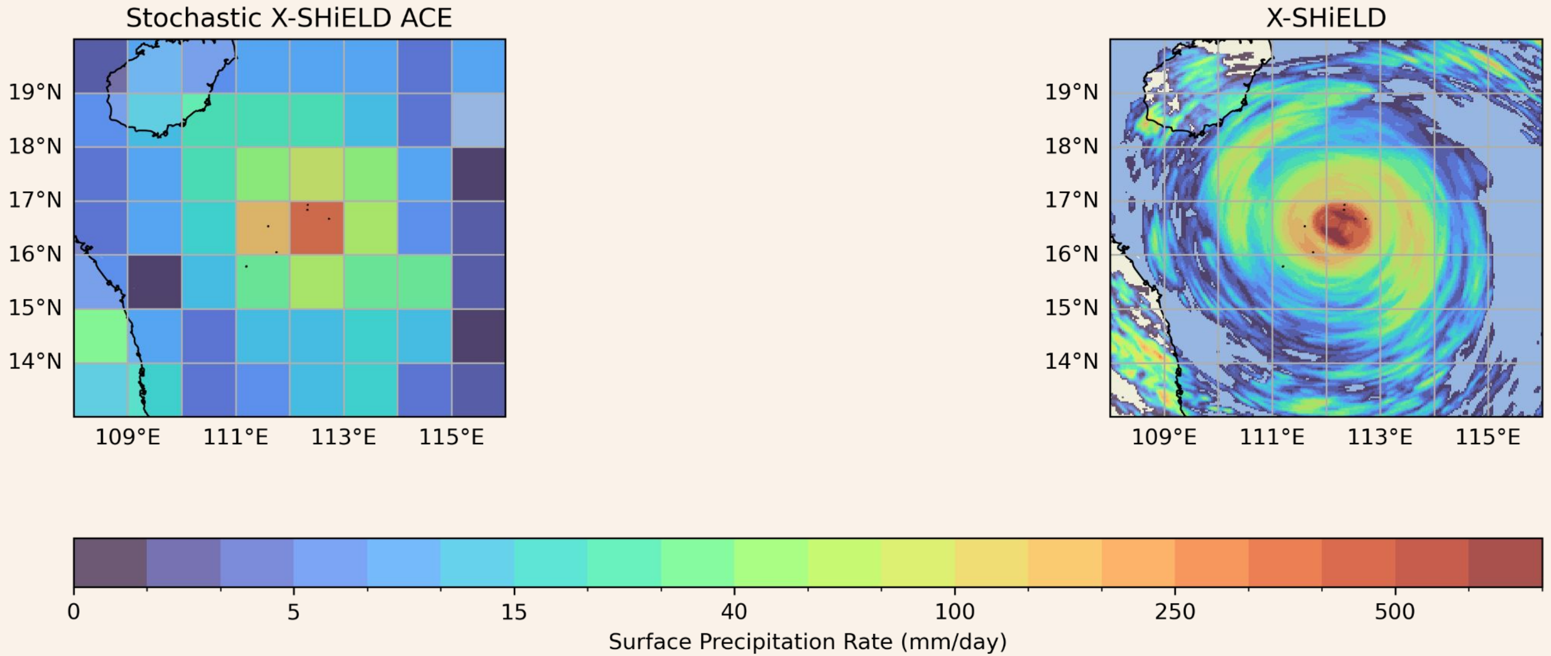
Emulating Climate Across Scales with Conditional Spherical Fourier Neural Operators

Oct 30, 2025

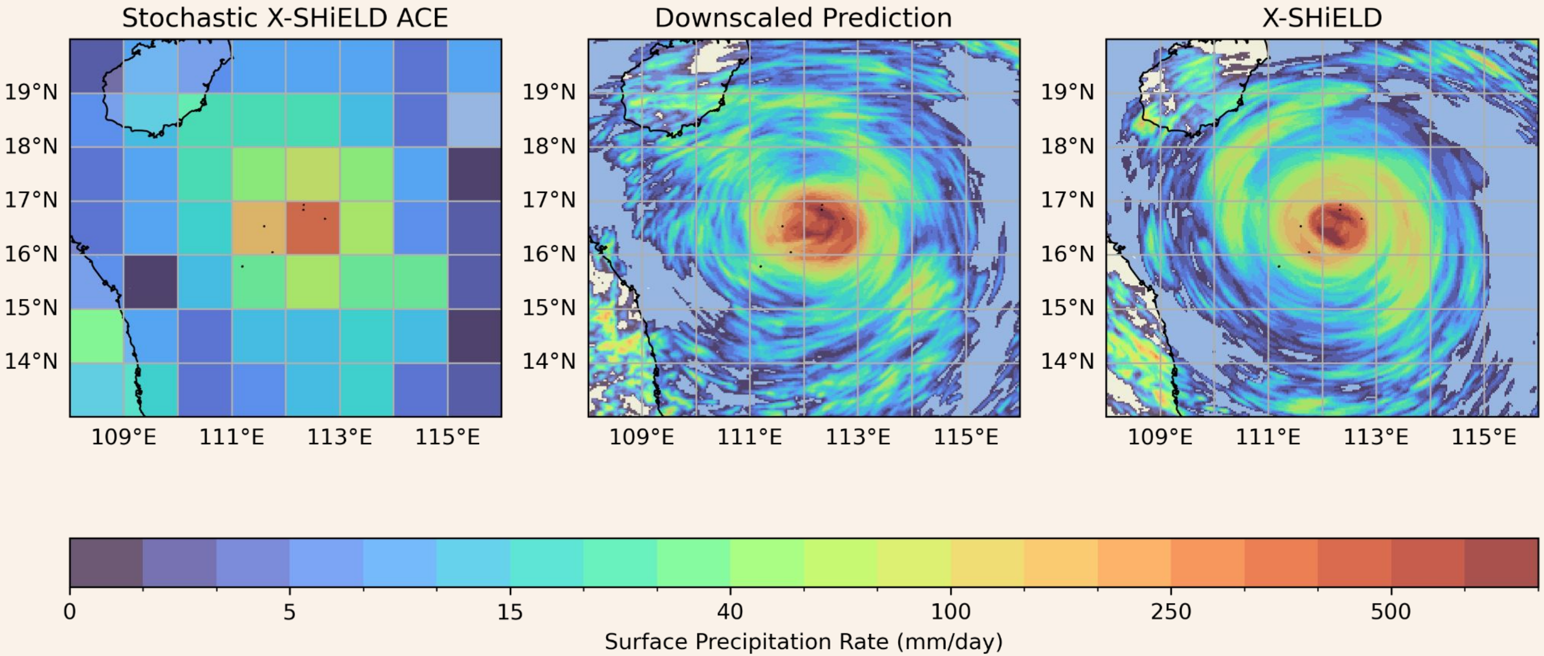
Ai2

Downstream Application: Downscaling

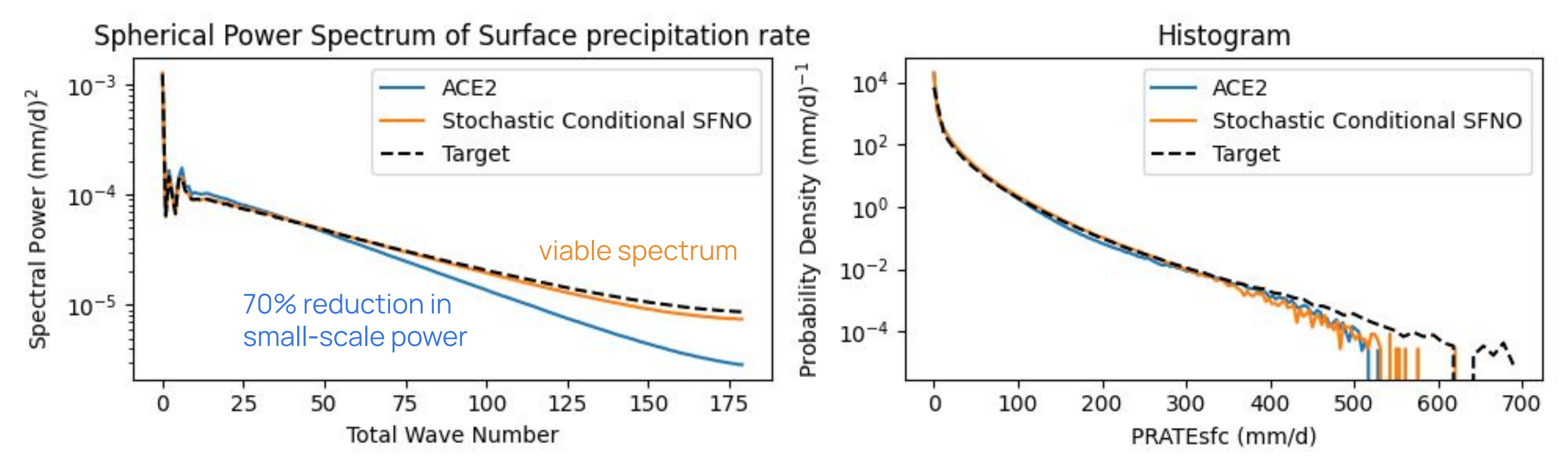


Results

Downstream Application: Downscaling



Deterministic vs Stochastic power spectra

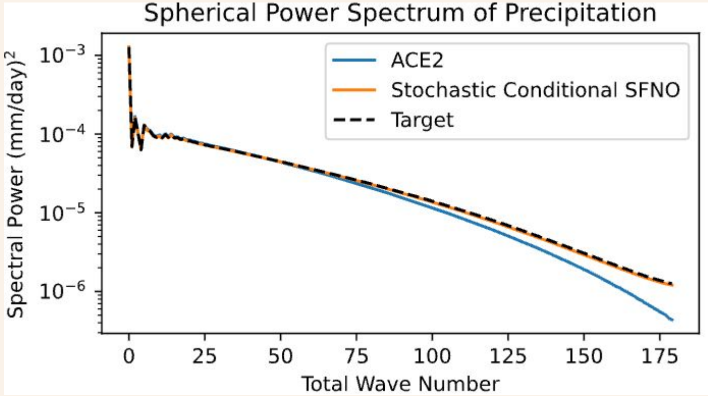


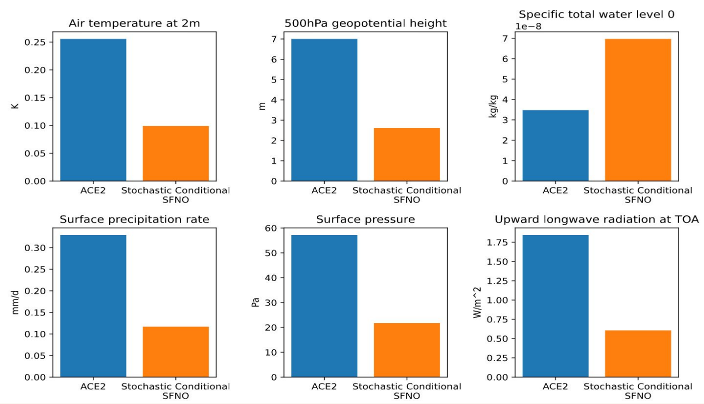
X-SHiELD training and evaluation
(based on ERA5 pre-training for both)

Ai2

Promising climate results on c96-shield

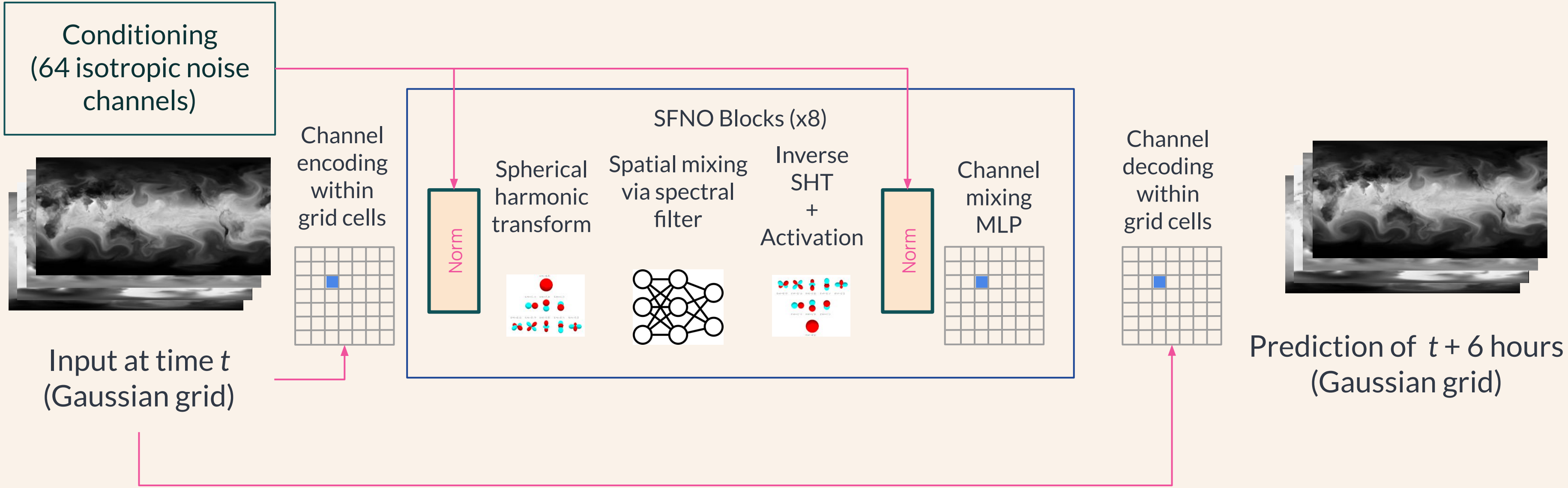
- Our base configuration worked well off the bat for C96 - AMIP data
  - Used a heavy weighting of Energy Score (ES) with a **90 % ES and 10% CRPS**
  - **Isotropic** noise
  - Pre-training on 1 - step then multi-step FTing with a **specified distribution**
- This dataset is fairly large, and has less small-scale power than other datasets



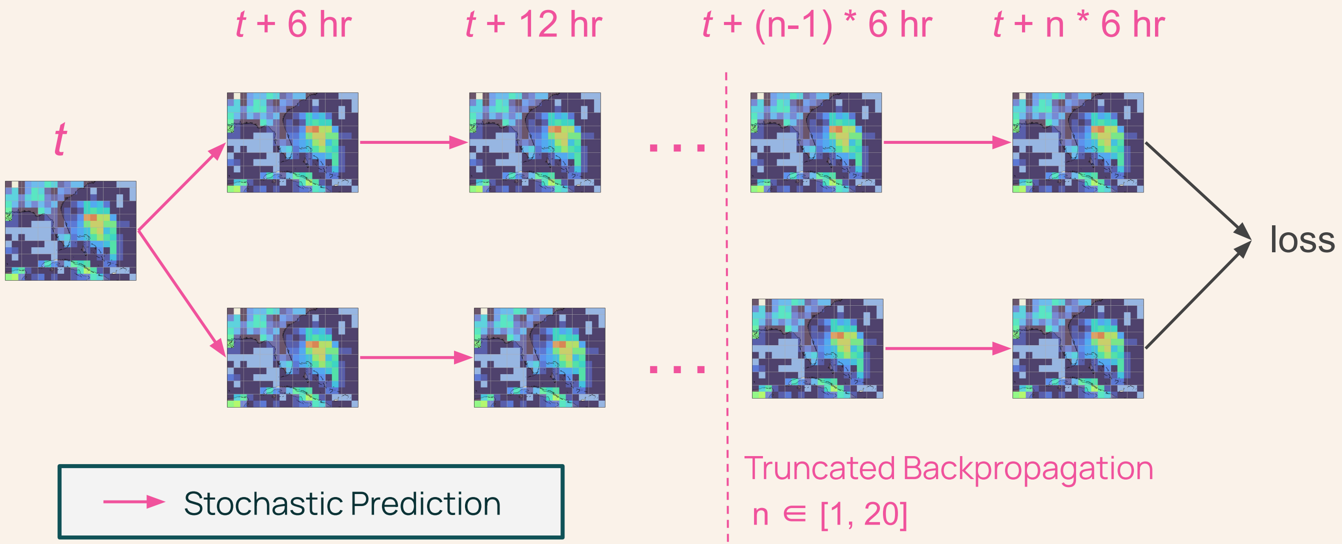


What did we do?

Conditional SFNO Architecture



Training



Initial training has n=1, then we fine-tune for up to 20 steps

Loss Function

“Almost fair” CRPS combined with reweighted energy score.

Energy score weighting set to give similar magnitude to CRPS, and independence from domain size.

$$L(F, y) = 0.1 \cdot \text{afCRPS}_{0.95,2}(F, y) + 0.9 \cdot \frac{2}{\sqrt{n_l n_m}} \text{ES}(\text{SHT} \circ F, \text{SHT}(y))$$

$$\text{afCRPS}_{\alpha,M}(F, y) = \mathbb{E}_{X \sim F}[|X - y|] - (1 - \frac{1-\alpha}{M}) \frac{1}{2} \mathbb{E}_{X, X' \sim F}[|X - X'|]$$

$$\text{ES}(F, \vec{y}) = \mathbb{E}_{\vec{X} \sim F}[\|\vec{X} - \vec{y}\|] - \frac{1}{2} \mathbb{E}_{\vec{X}, \vec{X}' \sim F}[\|\vec{X} - \vec{X}'\|]$$

Take-away points

- We have a successful strategy for fine-tuning a model usable for downscaling
- Optimizing over longer rollouts improves climate skill
- Optimizing spectral coefficients via energy score corrects small-scale spectral power