Generative Modeling of High-resolution Global Precipitation Forecasts

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Paper: tinyurl.com/precip-gan

Precipitation forecasting

- Traditional numerical weather models suffer from:
  - **High computational cost**: Estimated 596 MWh/SY for a global 1km-scale weather model [T. Kurth, et al. 2022]
  - **Inaccurate precipitation extremes**: The “drizzling bias” [D. Chen, et al. 2021]
- Deep learning-based models have become increasingly skilled
  - Competitive or **superior accuracy** [J. Pathak, et al. 2022]
  - Multiple orders-of-magnitude **reduction in computational cost** [T. Kurth, et al. 2022], both in time and energy
    $\Rightarrow$ large **ensemble** predictions + forecast **inference**
- Yet DL-based precipitation forecasting is **still lacking** in:

1) fine-scale details
2) accurate prediction of extremes

Generative modeling of precipitation

Generative adversarial networks (GANs) have recently shown promise to produce **realistic high-resolution local precipitation fields** [J. Leinonen, et al. 2020; S. Ravuri, et al. 2021; I. Price & S. Rasp, 2022].

Opportunities:

- Ability to generate **realistic-looking fine-scale details** on global scales.
- Better able to **handle the high sparsity and heterogeneity** that comes with precipitation data.

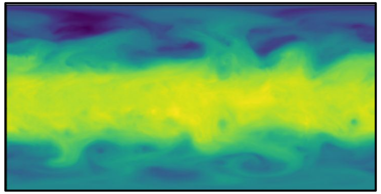
Challenges:

- While realistic-looking, GAN **"hallucination"** may lead to poorly-calibrated predictions.
- GANs are notorious for **distributional collapse**, leading to insufficient exploration of climate variability.

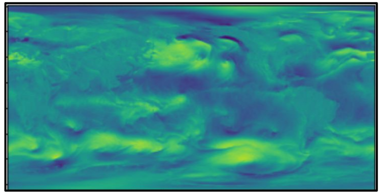
Inputs

ERA5: Fifth generation ECMWF global reanalysis dataset

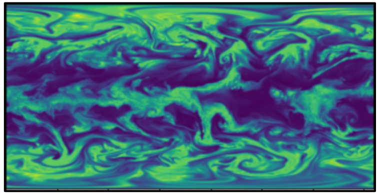
- 21 “scaffolding” variables, various vertical levels
- 0.25° lat x lon = 720 px by 1440 px



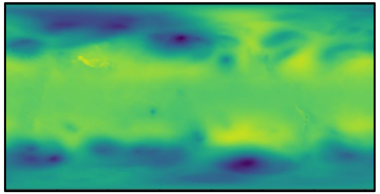
Temperature



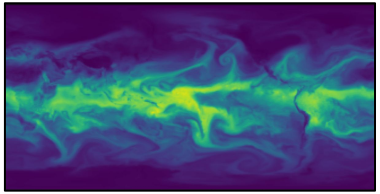
Wind velocities



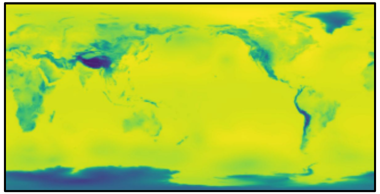
Relative humidity



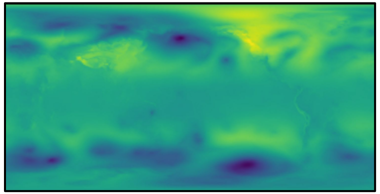
Geopotential



Total column water vapor



Surface pressure



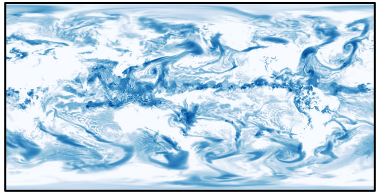
Mean sea-level pressure

- **Training**: 1979 – 2015 | **Validation**: 2016 – 2017 | **Testing**: 2018
- Δt = 6 hrs

Our GAN Precipitation Framework

We employ a recent **image-to-image translation** network [L. Jiang, et al. 2020] to predict global precipitation fields at 0.25° resolution.

Target:

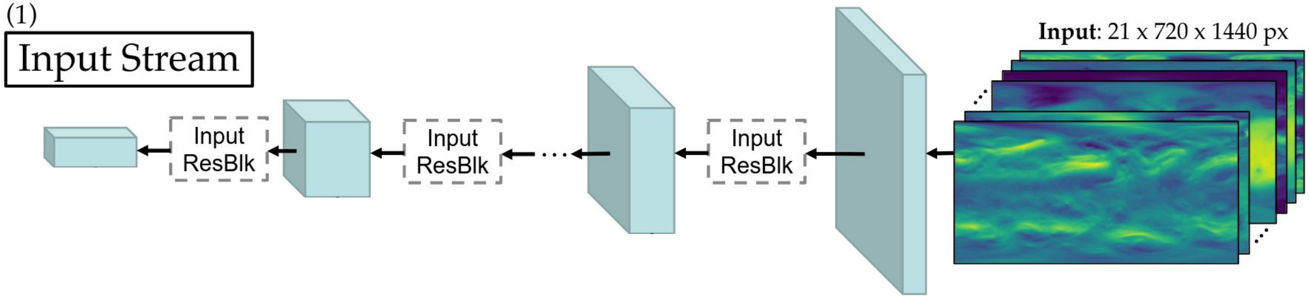


Total precipitation (6 hour accumulated)

The network has 4 components:

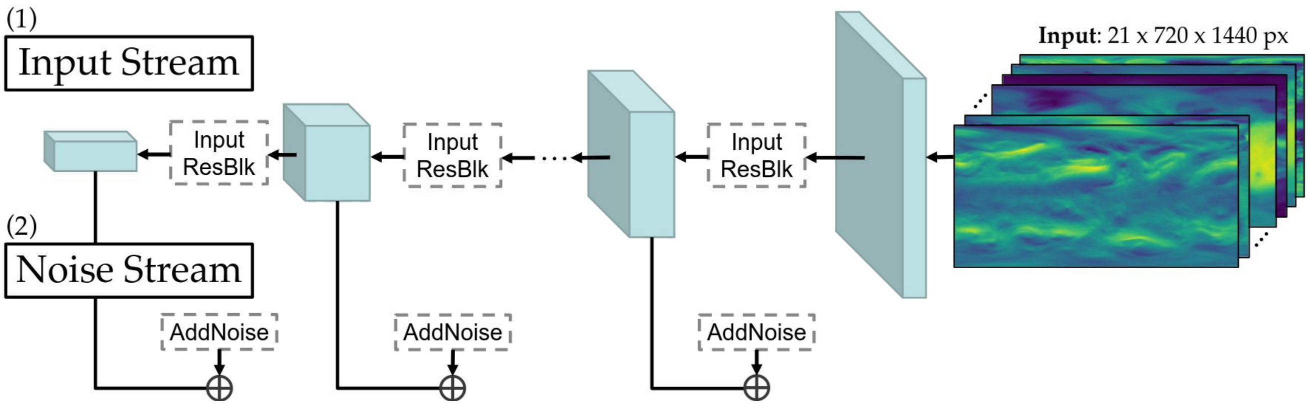
1) Input Stream
2) Noise Stream
3) Generator
4) Discriminator

Input Stream



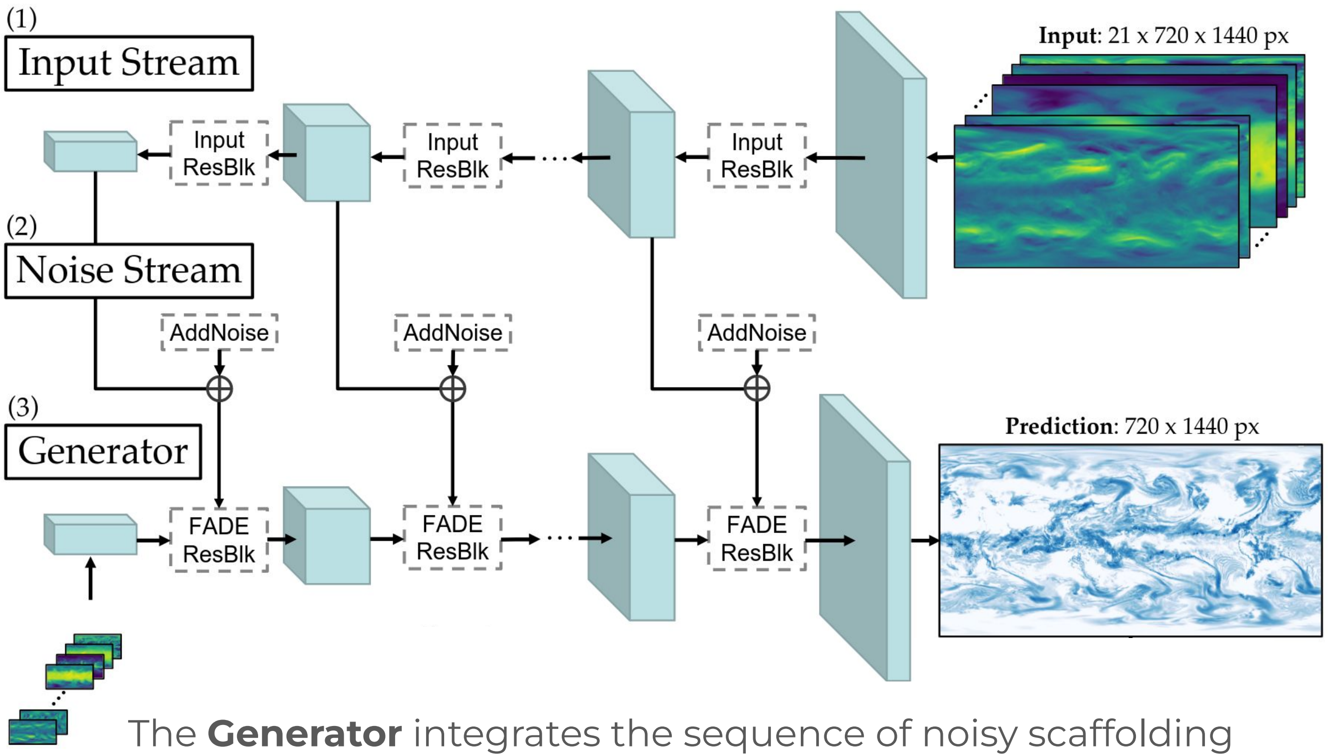
The **Input Stream** provides multi-scale representations of the 21 scaffolding variables.

Noise Stream



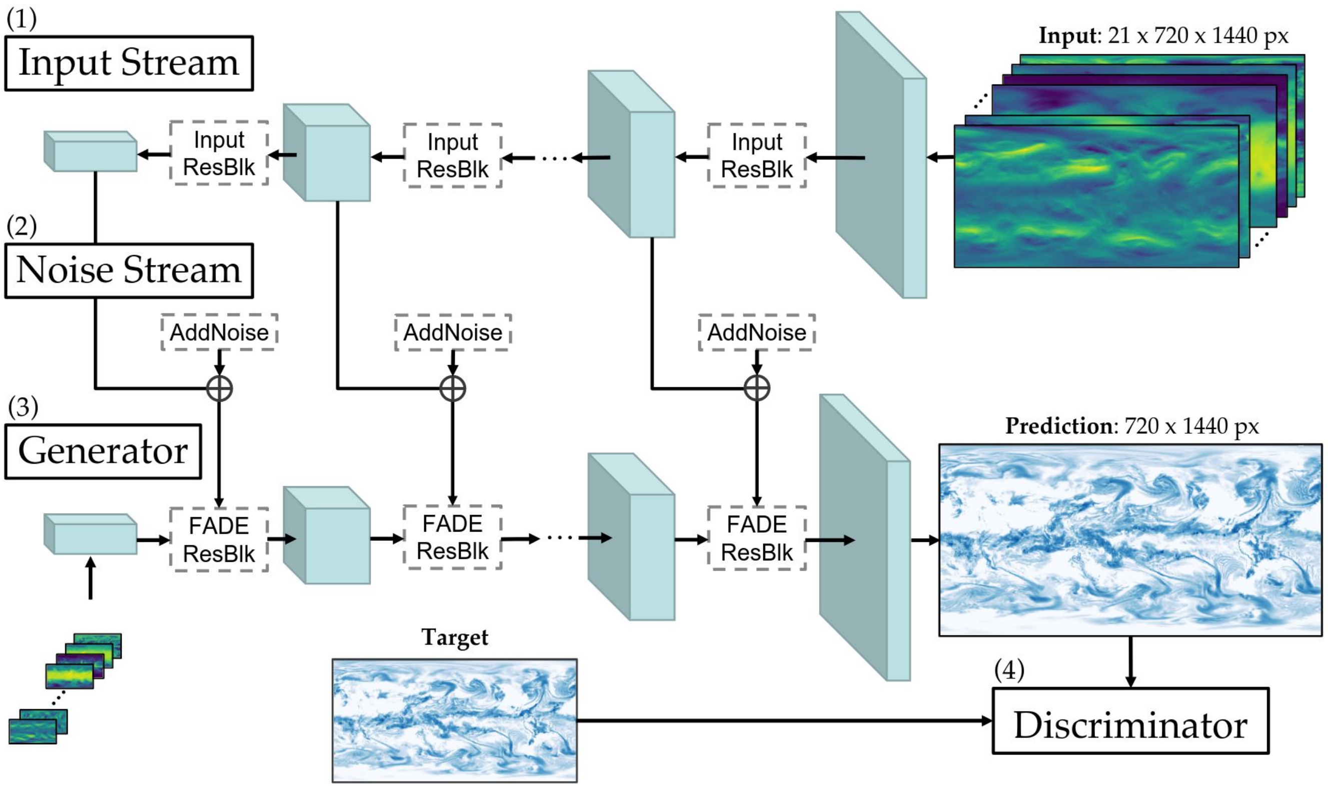
The **Noise Stream** helps prevent distributional collapse by injecting randomness into the scaffolding representations.

Generator

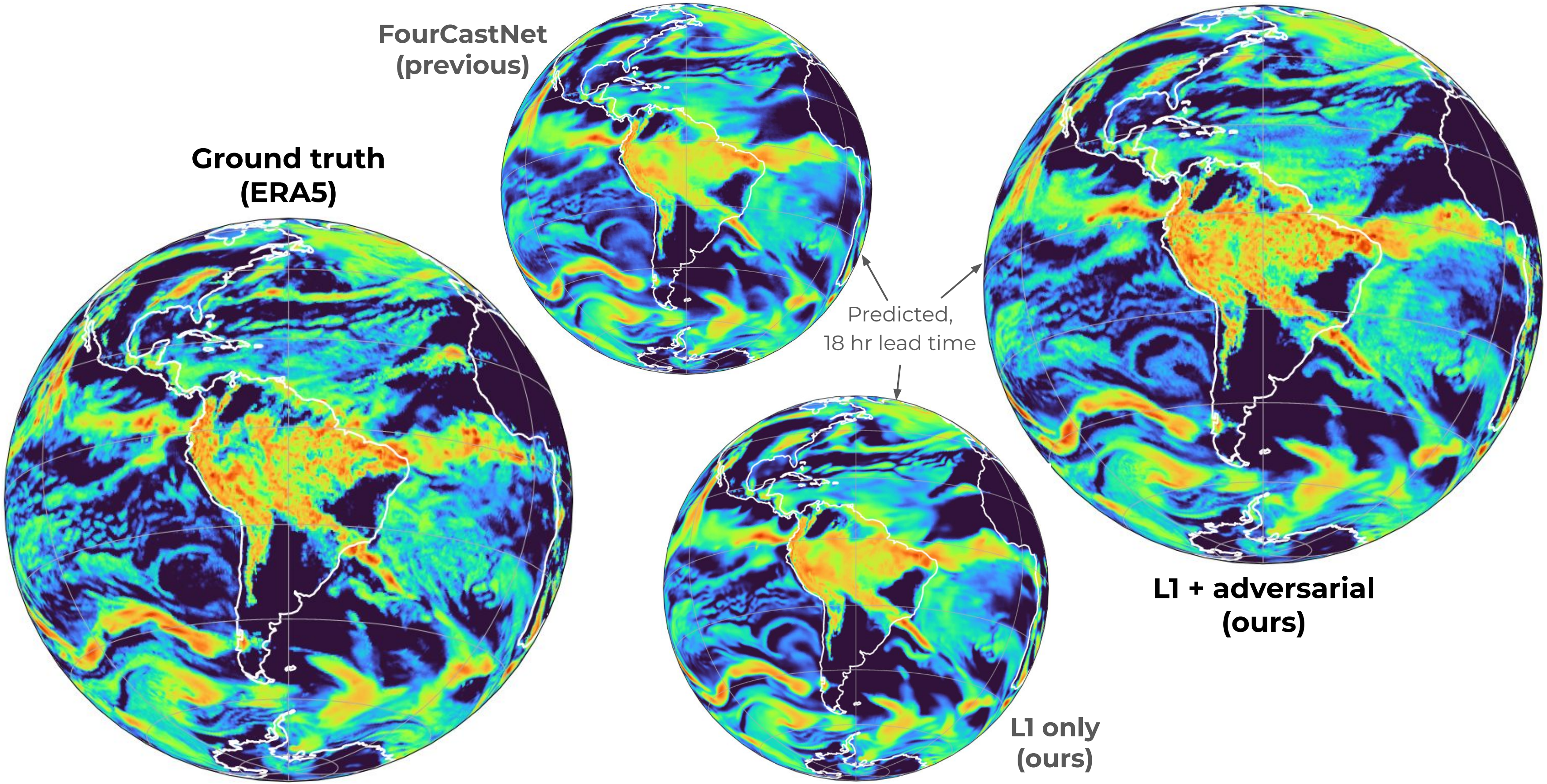


The **Generator** integrates the sequence of noisy scaffolding variable representations, working from coarse to fine scales.

Discriminator

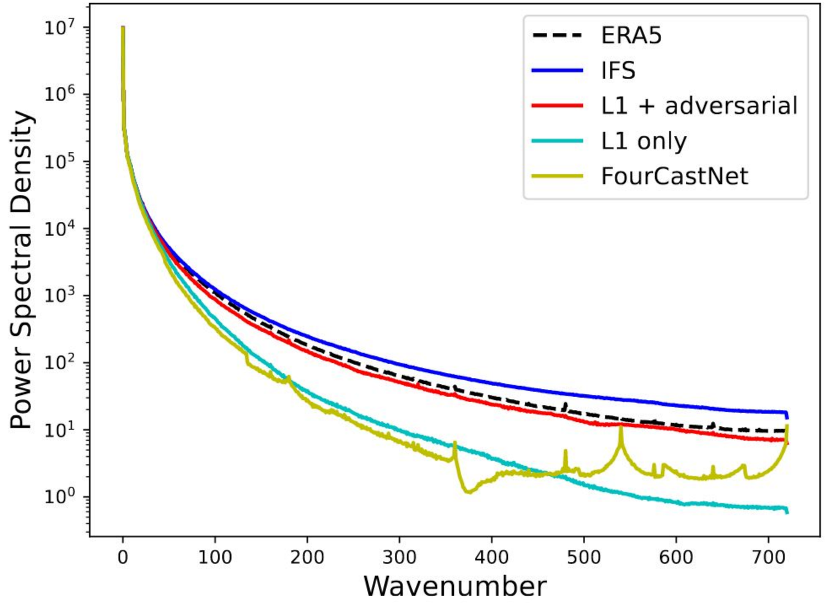


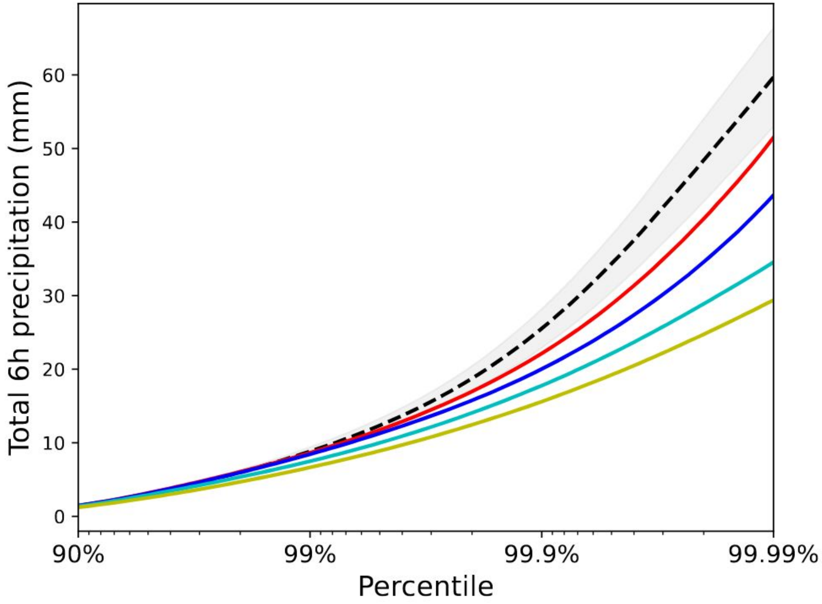
Results – Fine-scale details



Results – Extremes

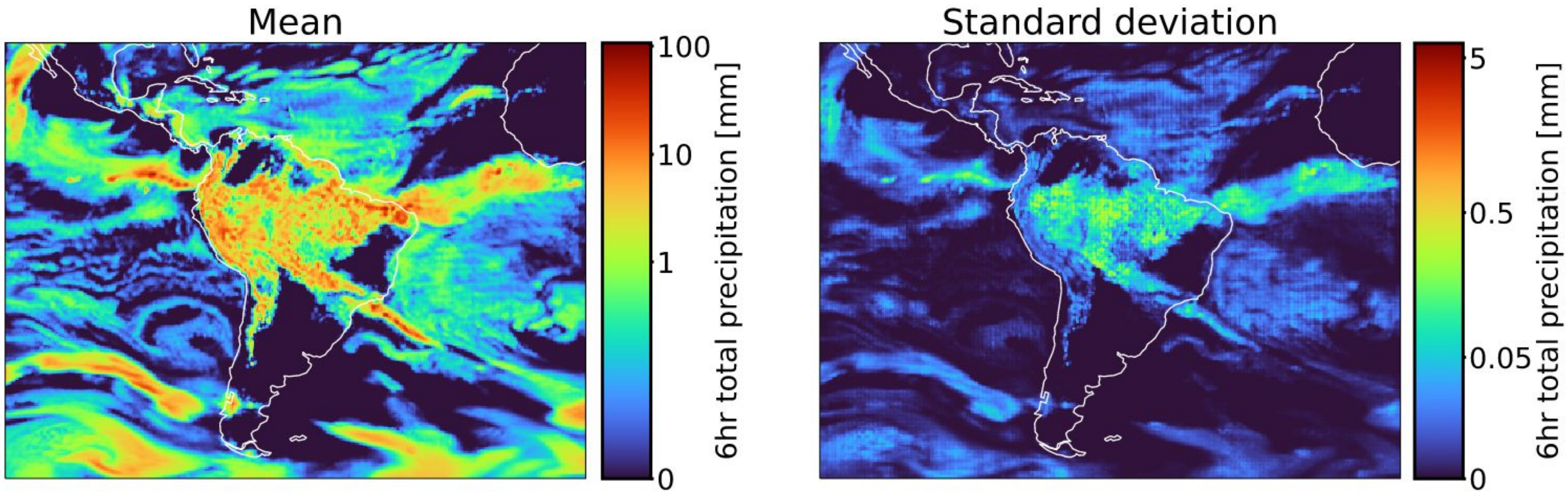
Predicted, 18 hr lead time





Ensemble Predictions

100-member ensemble mean and SD fields



Conclusions

- We extended FourCastNet with a GAN precipitation network, leading to promising improvements in fine-scale detail and precipitation extremes.
- We plan to explore further opportunities for improvement:
    - Integrate recent work to improve the stability of FourCastNet predictions for longer time horizons.
    - Use variational methods to increase diversity of generated outputs for higher accuracy and ensemble-based inference.

Thank you!

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