



# Loosely Conditioned Emulation of Global Climate Models With Generative Adversarial Networks

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# Introduction

- Climate models encapsulate our understanding of the Earth system
  - Allows research on future realizations of Earth
  - Estimating risks of extreme weather events requires numerous realizations
- Current climate models are computationally expensive (days to months)
- Deep learning can provide a solution:
  - Train a Generative Adversarial Network (GAN) to emulate Earth System Models (ESMs)
  - Generate realizations rapidly («1s)



# Data

- Daily global precipitation output from the MIROC5 ESM
  - 725, 45, and 45 years of ESM data for train, validation, and test
  - Model 32-day sequences (“months”)
  - Two models, loosely conditioned by training on disjoint boreal “seasons”
    - Fall-Winter
    - Spring-Summer



# Problem Formulation

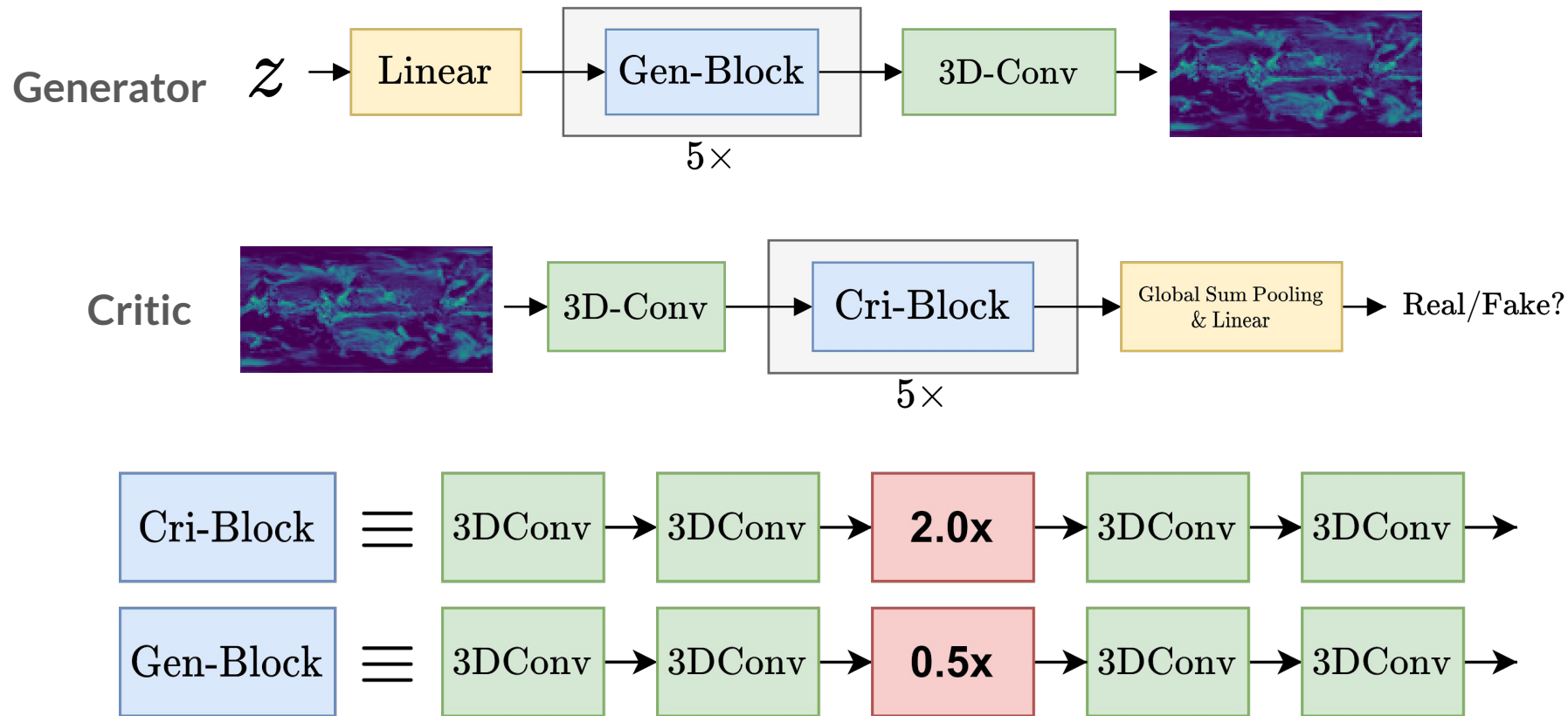
Real data:  $x \in \mathbb{R}^{32 \times 64 \times 128} \sim P$

Train a GAN to induce a distribution  $G$  that approximates  $P$

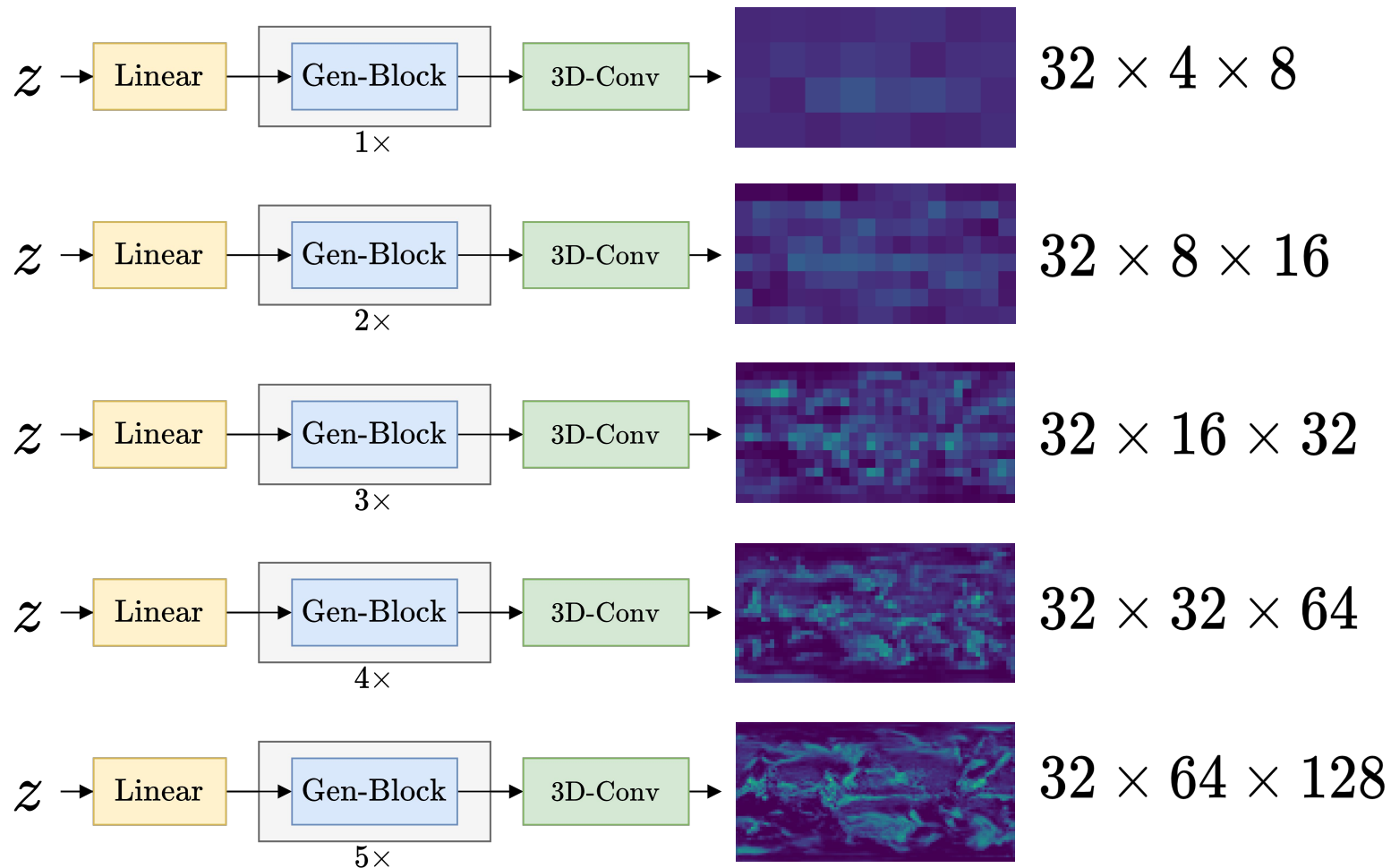
Performance metrics:

- Compare mean number of dry days in samples from  $G$  vs  $P$
- KL-divergence-based scores between  $G$  and  $P$

# Model Architecture



# Progressive Growing

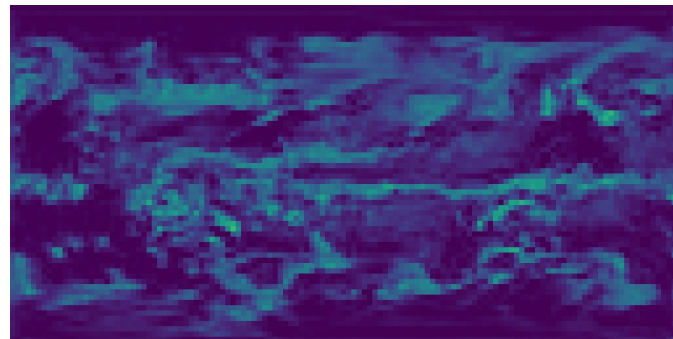
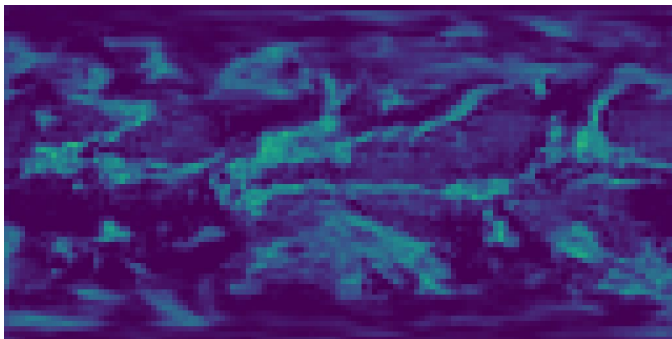


# Samples

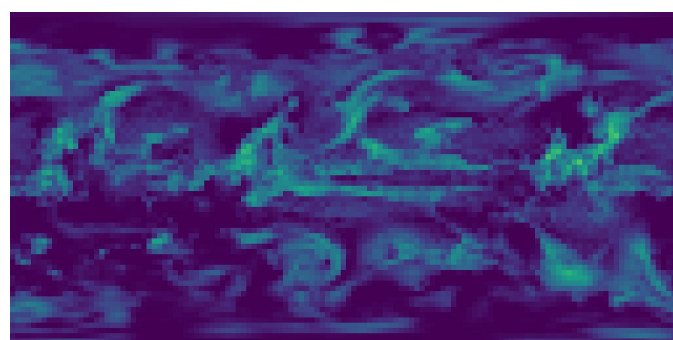
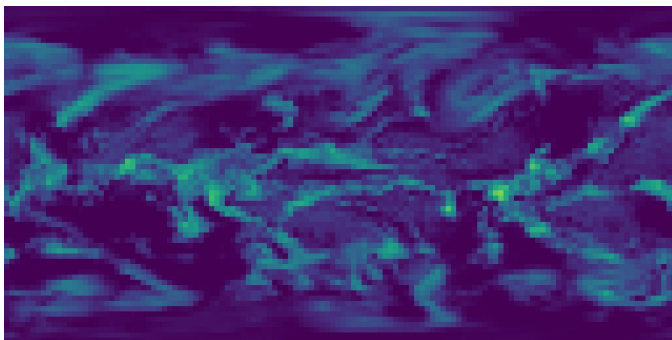
Fall-Winter

Spring-Summer

Generated

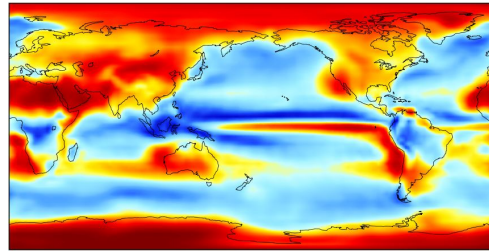


Real

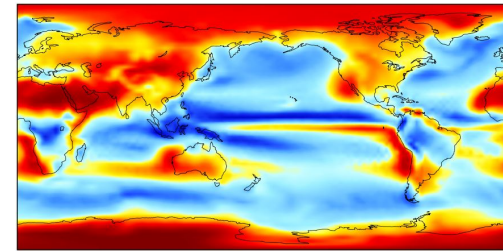


# Mean Number of Dry Days

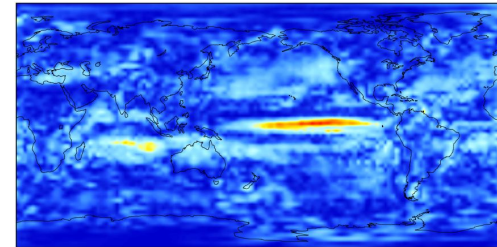
- Averaged per-sample across ~8000 months
- Performs well globally
- Slightly wider dry tongue near equator



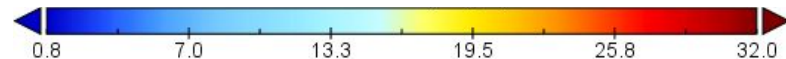
a) Generated



b) Test



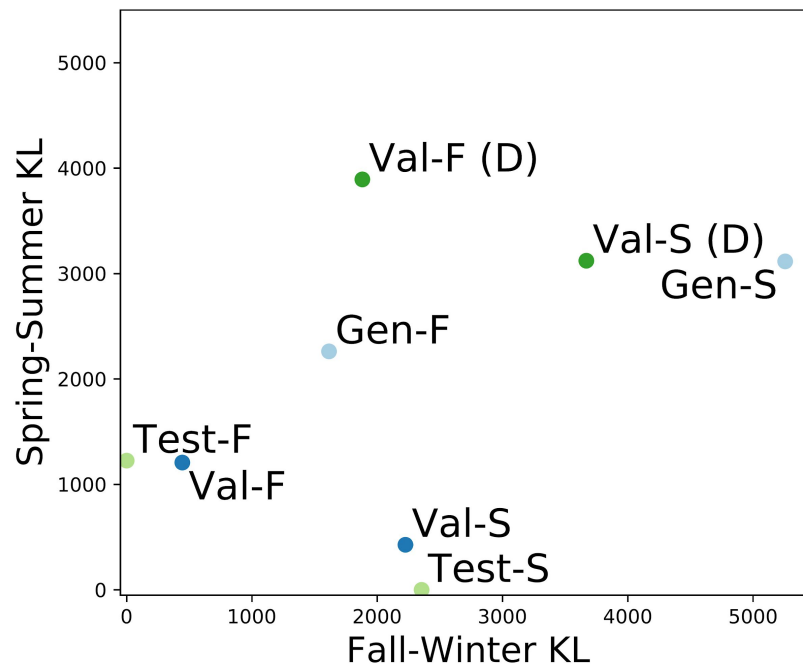
c) Absolute Difference





# KL Divergence

- **X-axis:** KL-Div against Fall-Winter Test Set
- **Y-axis:** KL-Div against Spring-Summer Test Set
- Degrade validation sets by applying zero-centered noise
  - Serves as our upper bound
- Generated data differs by a variance of 0.024 mm/Day (less than 1% off)



$$\text{Val (D)} = \text{Val} + \epsilon$$
$$\epsilon \sim N(0, 0.024)$$



# Conclusion

- Take-away:
  - GANs can generate realistic spatio-temporal precipitation
- Future work:
  - Joint generation of precipitation and temperature
  - Conditioning on low temporal resolution climate averages