Improving East African precipitation forecasts using a generative machine learning model

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Image: Google Maps

Image: Google Maps

Region

- Equatorial East Africa.
- Prone to severe drought, and heavy rains leading to flooding.
- Heterogeneous: Lake Victoria, Mountainous areas, coastal areas, rainfall seasons.
- Dominated by convective rainfall.
- Conventional precipitation forecasts tend to perform poorly in this region
    - Diurnal cycle
    - Rainfall intensity

Nicholson, Sharon E. "Climate and climatic variability of rainfall over eastern Africa." *Reviews of Geophysics* 55.3 (2017): 590-635..

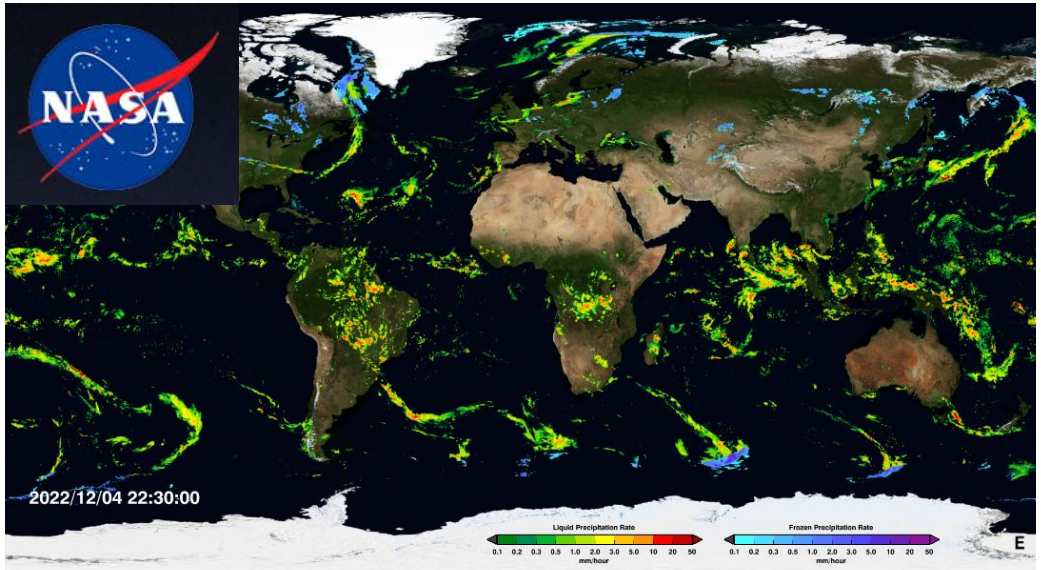
Vogel, Peter, et al. "Skill of global raw and postprocessed ensemble predictions of rainfall over northern tropical Africa." *Weather and Forecasting* 33.2 (2018): 369-388.

Aims / motivation

- Historically, forecast skill in this and similar regions has been low.
- Can machine learning techniques improve the quality of these forecasts?
- Do these models allow us to better forecast extreme rainfall events?
- How well do machine learning models cope with convective rainfall?
- Provide input to World Food Programme / Oxford / Google joint workshop in Kenya (May 2023).

Data

- Observational: IMERG
  - Satellite observations of microwave and infrared, calibrated against rain gauges.
  - Hourly
  - 0.1 x 0.1 degrees resolution



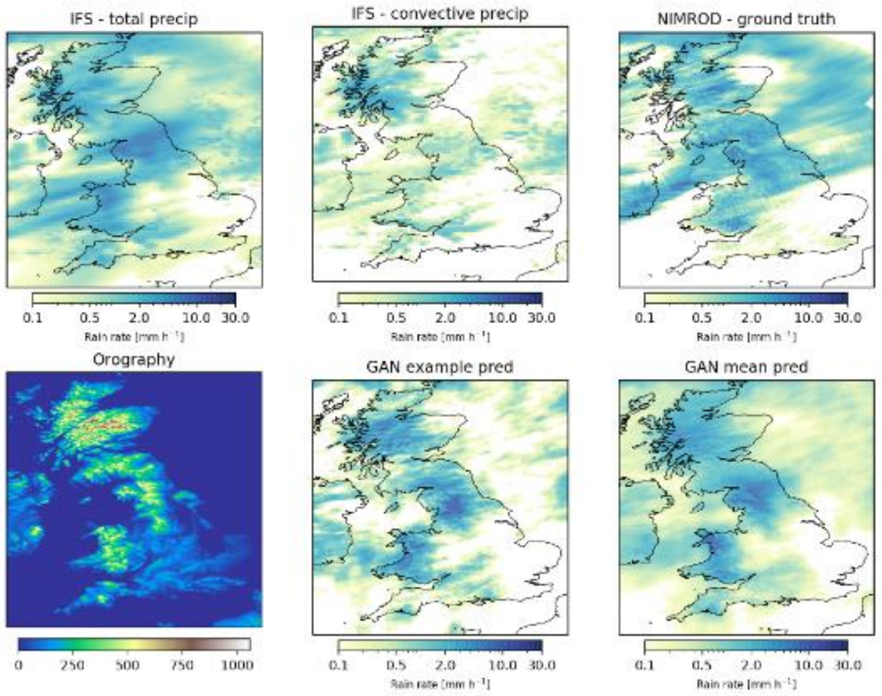
- Forecast: ECMWF IFS HRES
  - Hourly
  - 0.1 x 0.1 degrees resolution

ECMWF

- Training: March 2016 – March 2018
- Validation: June 2018 – June 2019

Modelling approach

- Using a “conditional Generative Adversarial Network” (Leinonen et al, Harris et. al.)
- 6-18h lead time
- Inputs: forecast variables + land-sea mask + orography



Leinonen, J., Nerini, D., & Berne, A. (2020). Stochastic super-resolution for downscaling time-evolving atmospheric fields with a generative adversarial network. *IEEE Transactions on Geoscience and Remote Sensing*, *59*(9), 7211-7223.

Harris, L., McRae, A. T., Chantry, M., Dueben, P. D., & Palmer, T. N. (2022). A generative deep learning approach to stochastic downscaling of precipitation forecasts. *Journal of Advances in Modeling Earth Systems*, *14*(10), e2022MS003120.

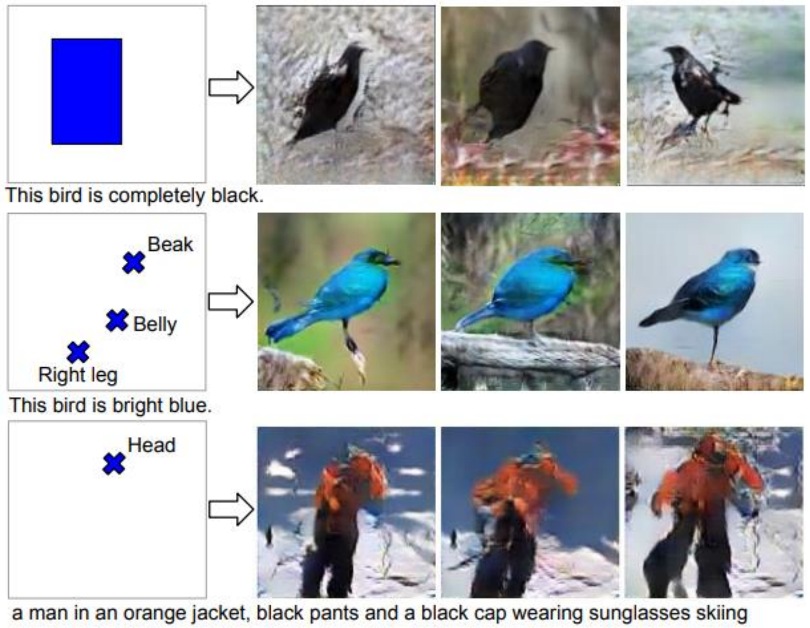
What is a generative model?

- Examples:

“A bowl of soup that looks like a monster made out of plasticine”

openai.com/dall-e-2/

Chat GPT

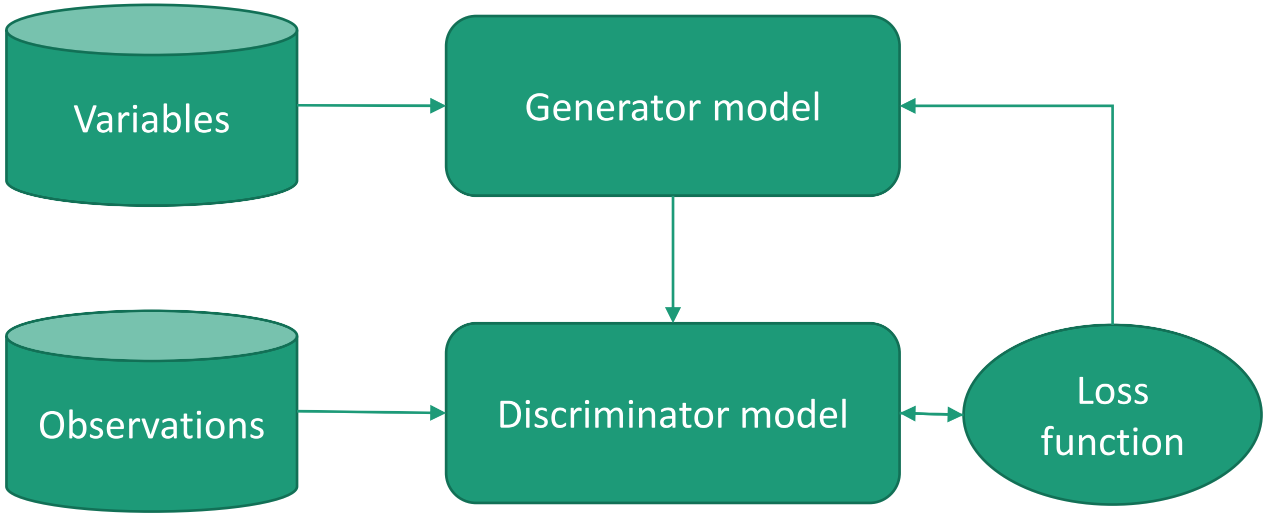


Reed, S. E., Akata, Z., Mohan, S., Tenka, S., Schiele, B., & Lee, H. (2016). Learning what and where to draw. *Advances in neural information processing systems*, *29*.

- Allows creation of an ensemble forecast
  - Quantify risk

Generative Adversarial Networks (GAN)

- Standard technique in image generation.
- Attempts to learn the **probability distribution** of images (given a prompt).



Goodfellow, et al. "Generative adversarial nets" *Advances in Neural Information Processing Systems*, 27, 2014

Generative Adversarial Networks (GAN)

Generator Data

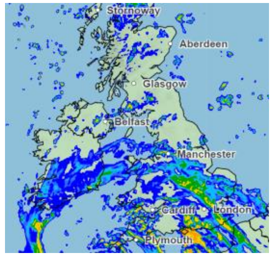
Discriminator

Real Data

"a cartoon drawing of a weather forecast of rain over the UK"

GENERATED

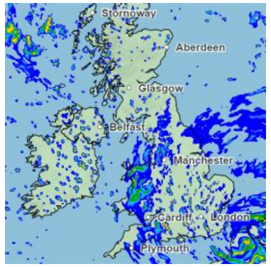
REAL

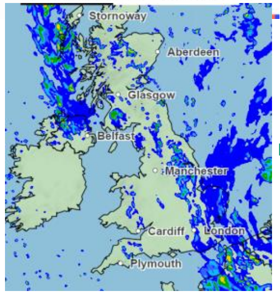


"a realistic weather forecast of rain over the UK"

GENERATED

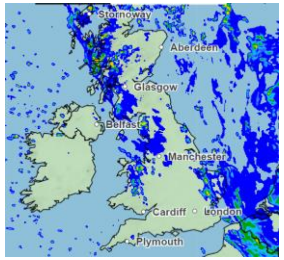
REAL





REAL

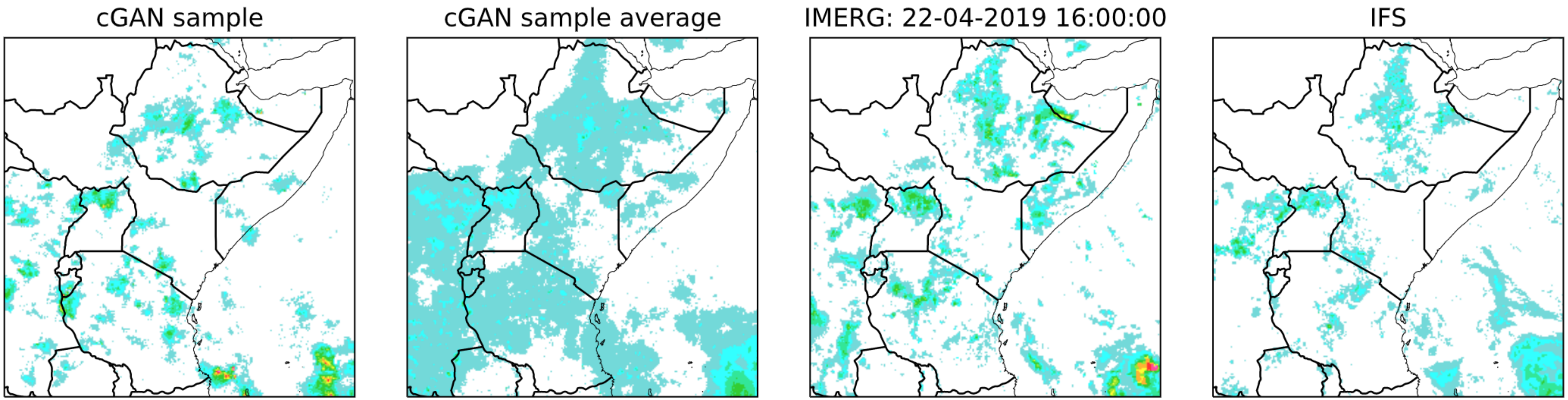
REAL



Generated images: Dall-E 2   Real images: Met Office

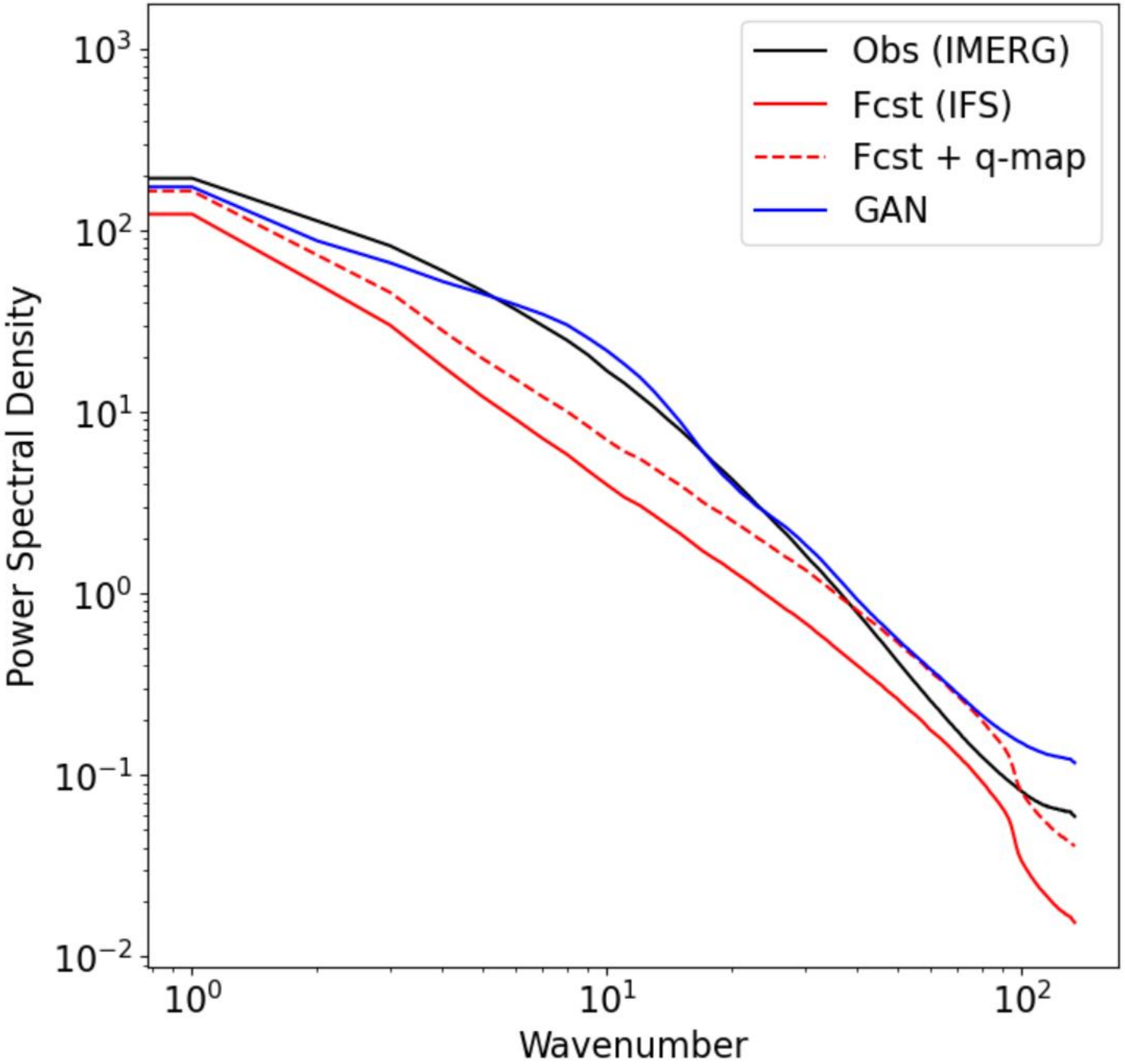
Preliminary results

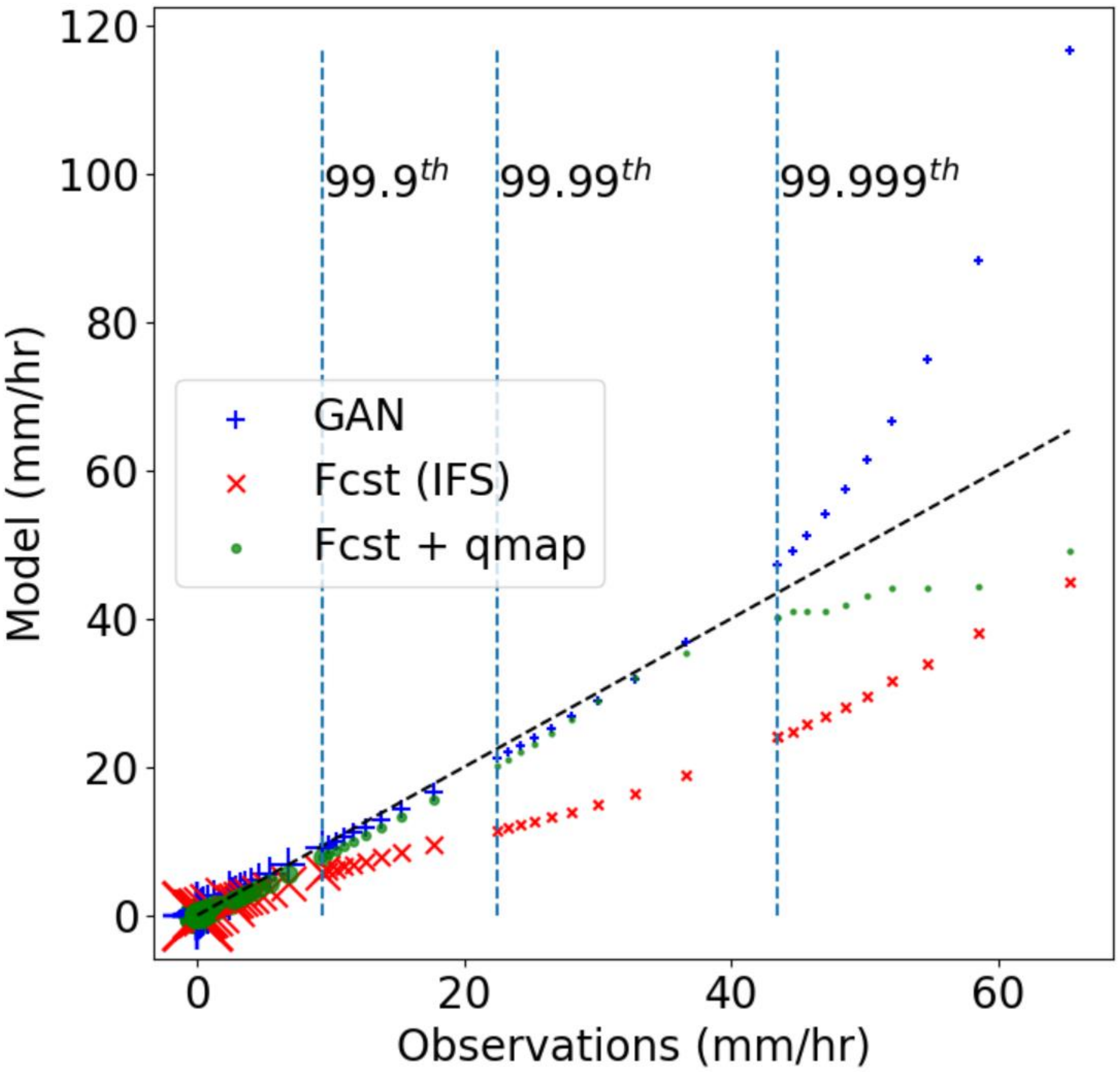
- Initially training on a small model, to find the best training parameters.



Preliminary results

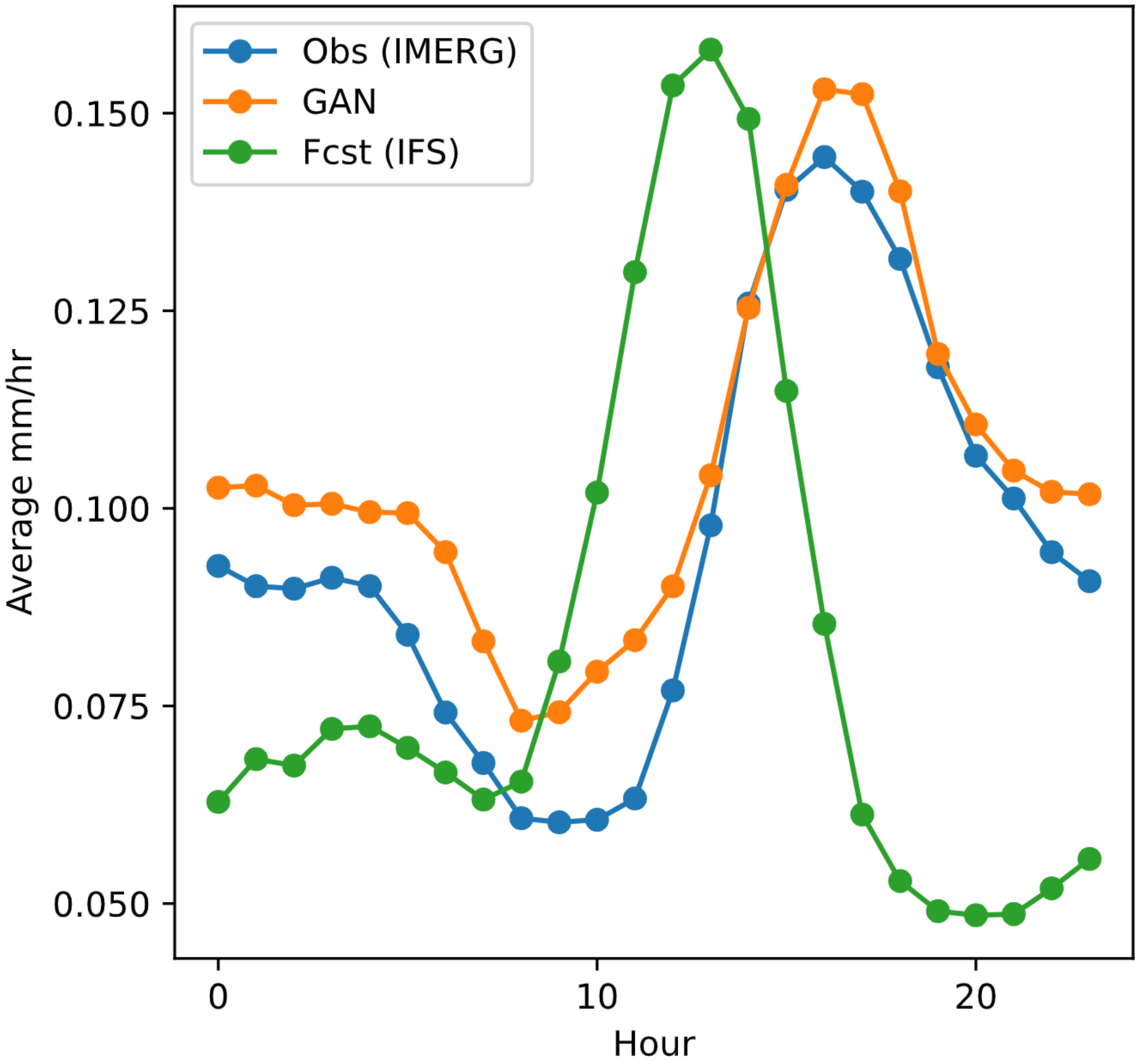
- Baseline: quantile-mapped IFS forecast





Preliminary results

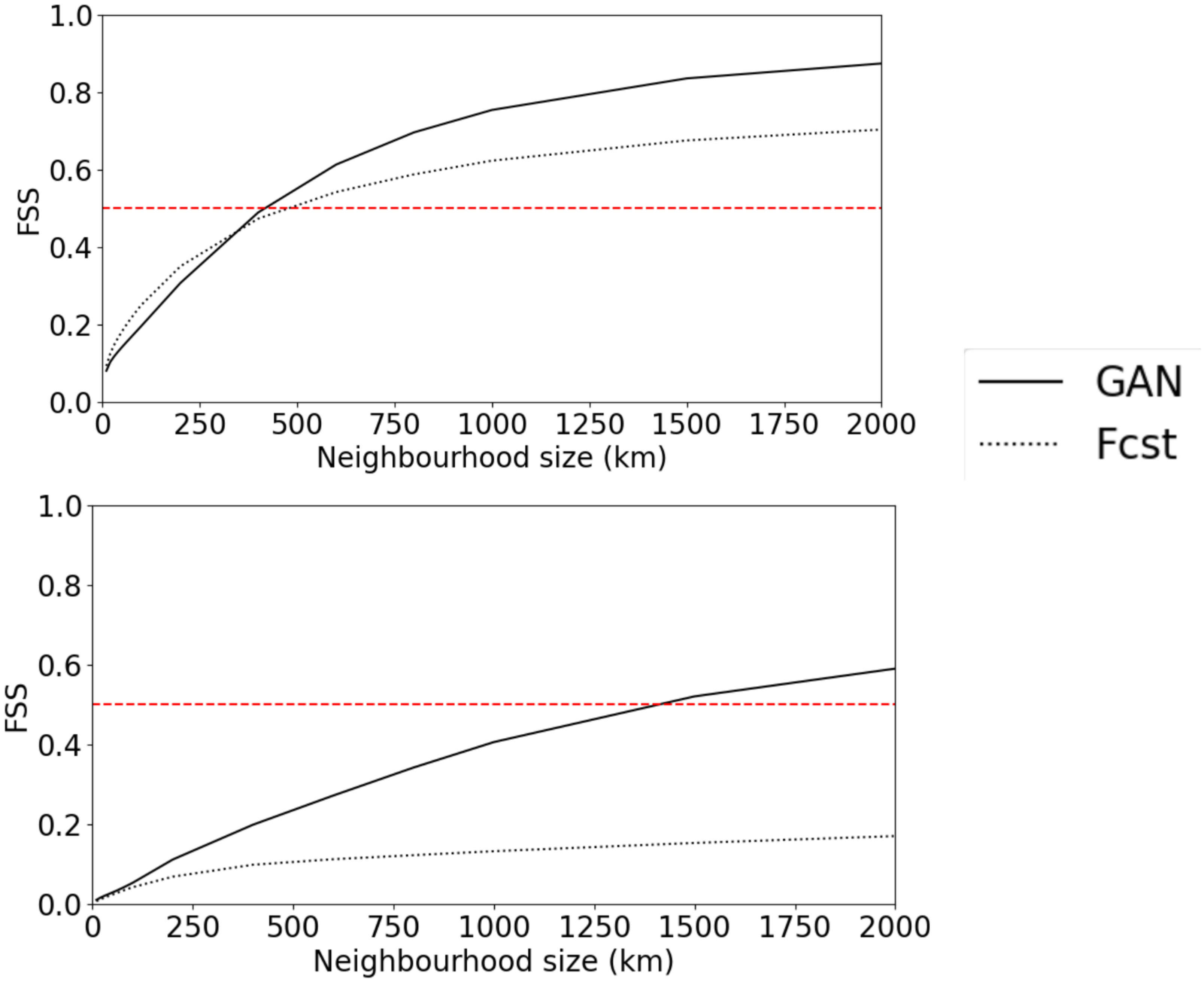
- Corrects the diurnal cycle



Preliminary results

Threshold = Median value

Threshold = 98.5th percentile



Summary

- Applying a GAN to postprocess rainfall forecasts
- Successfully improves several features of the forecast:
  - Diurnal cycle
  - Spatial distribution
  - FSS
- Tends to overpredict at very high percentiles

Thank you!

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