Spatially coherent postprocessing of cloud cover and precipitation using GANs

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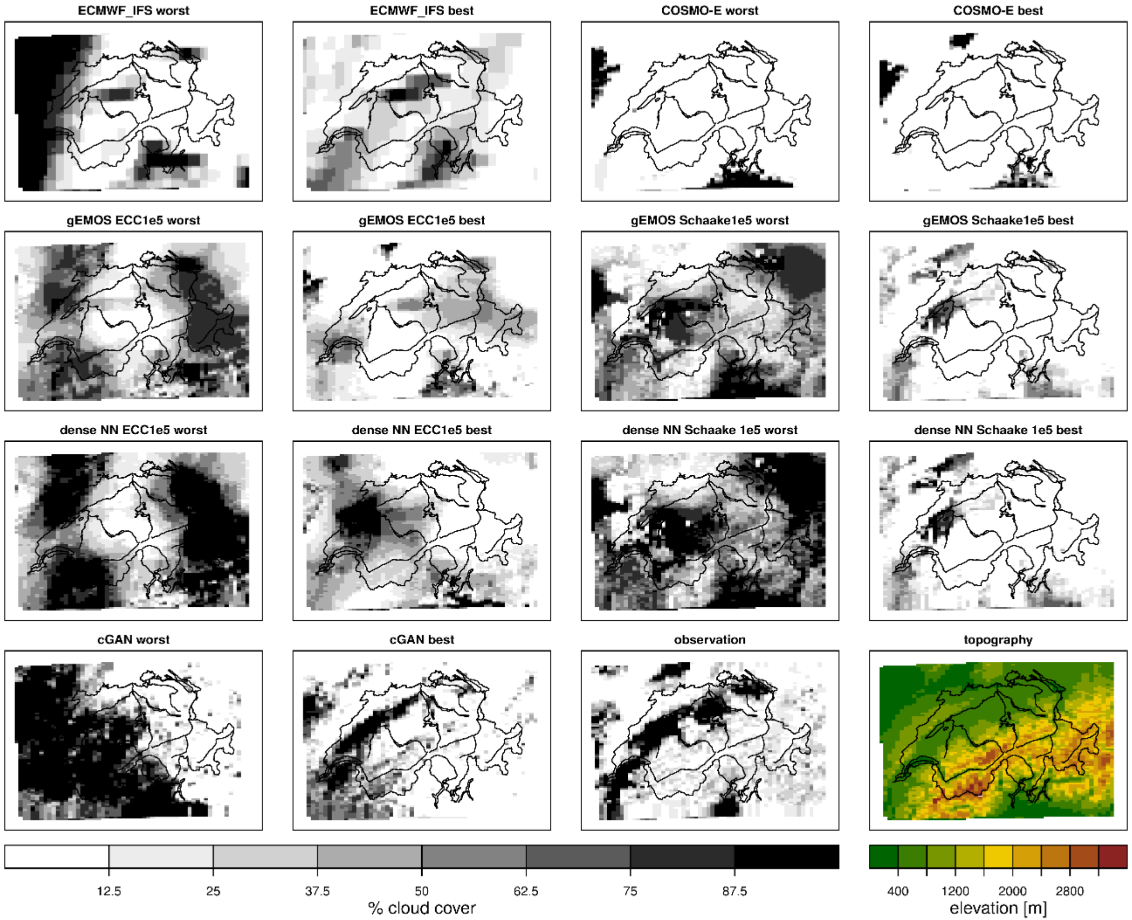
Overview

- Part 1: cGAN postprocessing for hourly **cloud cover** which actually **works**[1]
  - Reference forecasts: gEMOS or dense NN + ECC or Schaake shuffle
  - Univariate and multivariate calibration
  - Pros and cons of the different methods
- Part 2: cGAN postprocessing for **precipitation** which **does not work yet**
  - Reference forecasts: COSMO-E, spatially pooled COSMO-E, (similarity based) quantile regression

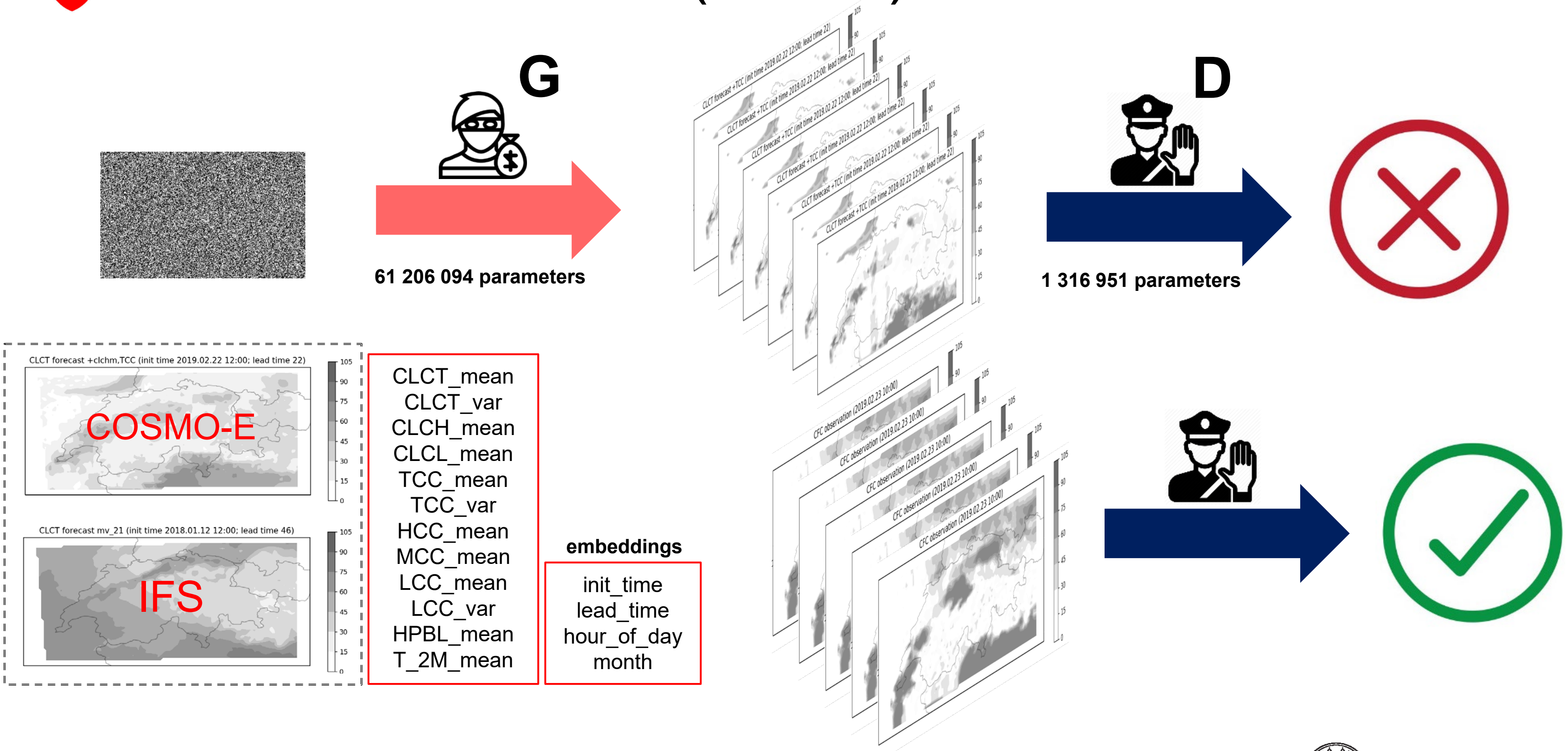
[1] *Dai, Y., & Hemri, S. (2021). Spatially coherent postprocessing of cloud cover ensemble forecasts. Monthly Weather Review, 149(12).*


ECMWF_IFS worst
ECMWF_IFS best
COSMO-E worst
COSMO-E best
gEMOS ECC1e5 worst
gEMOS ECC1e5 best
gEMOS Schaake1e5 worst
gEMOS Schaake1e5 best
dense NN ECC1e5 worst
dense NN ECC1e5 best
dense NN Schaake 1e5 worst
dense NN Schaake 1e5 best
cGAN worst
cGAN best
observation
topography
12.5
25
37.5
50
62.5
75
87.5
% cloud cover
400
1200
2000
2800
elevation [m]

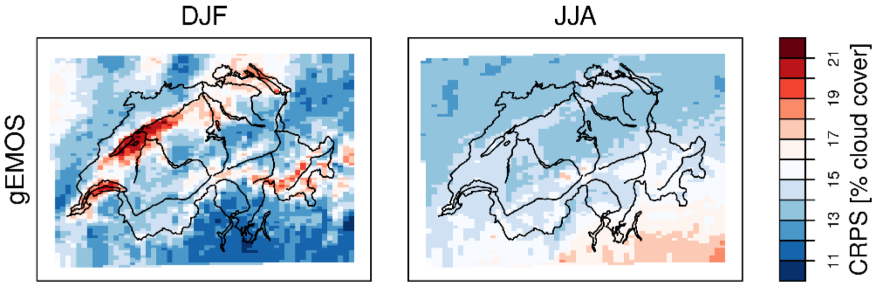
Dataset

- Predictors (subsampled)
  - Numerical forecasts (COSMO-E and IFS [+12h])
    - Training set: 05.2016 - 04.2018
    - Validation set: 05.2018 - 04.2019
    - Test set: 05.2019 - 04.2020
- Observations
  - EUMETSAT CM-SAF satellite data, 2 × 2 km resolution

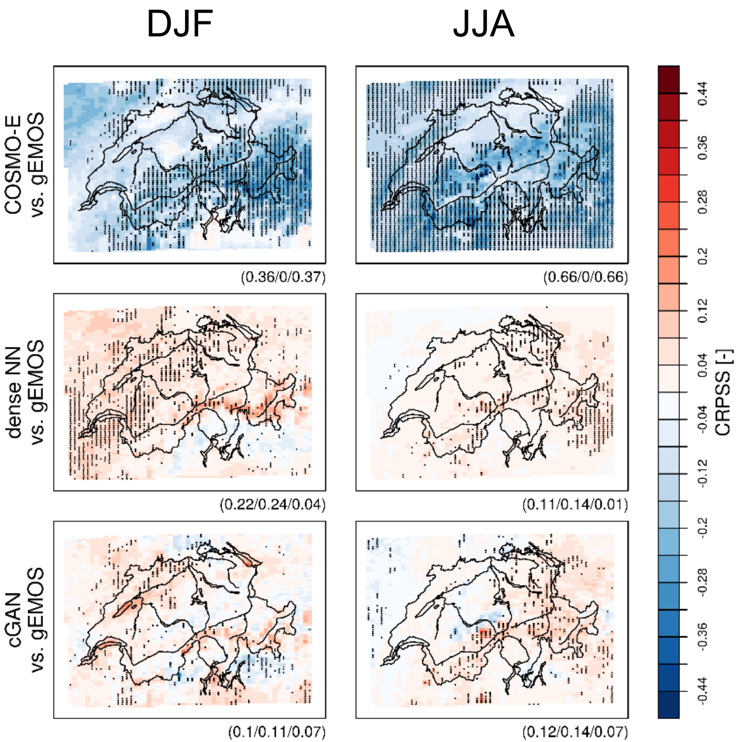
Conditional GAN (cGAN)



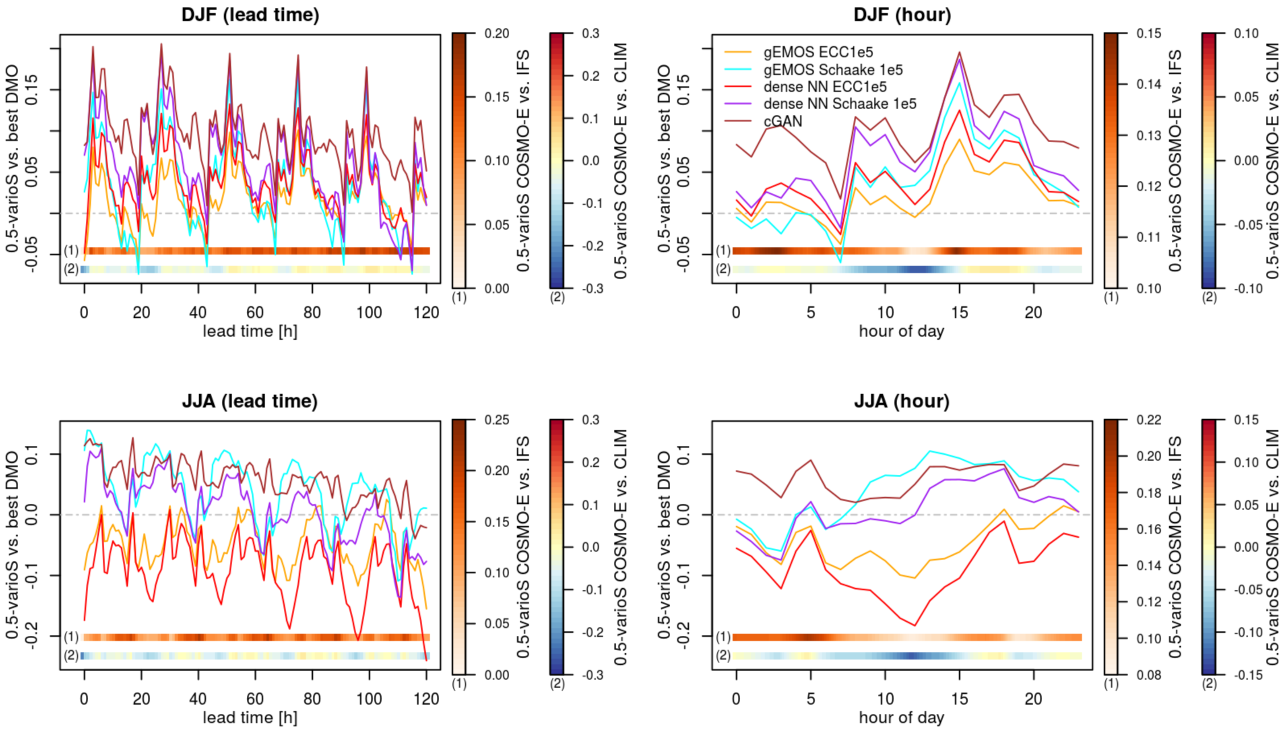
Forecast skill



- High DJF CRPS in fog prone regions
- gEMOS skill > COSMO-E skill, but not significantly in fog prone regions
- denseNN and cGAN improve forecast skill compared to gEMOS

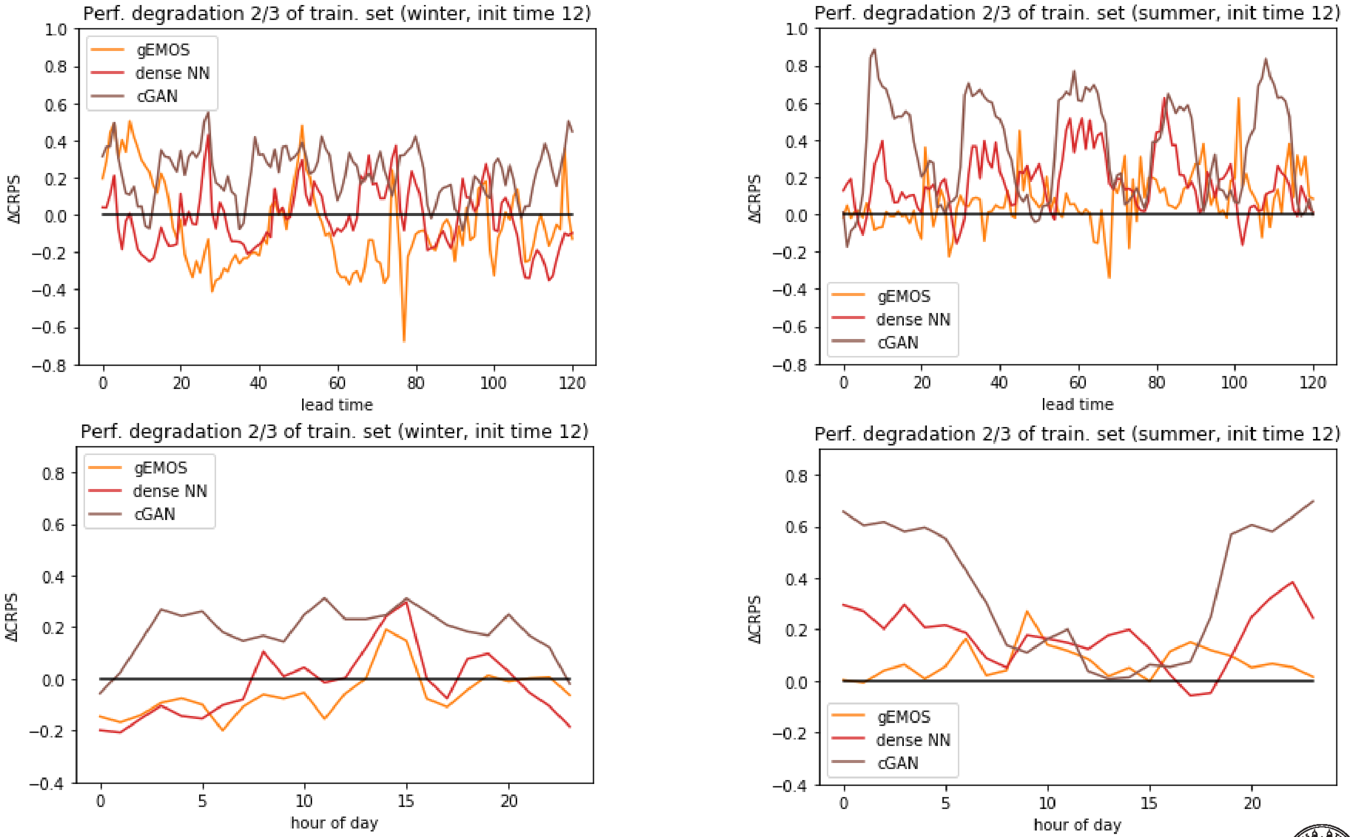


Multivariate verification



- p-variogram skill score
- cGAN performs best
- Schaake shuffle outperforms ECC for gEMOS and denseNN

Data efficiency



more data needed

University of Zurich[UZH]

ETH zürich

Summary part 1

- Three approaches for post-processing cloud cover

	gEMOS	Dense NN	cGAN
Interpretability	★★★☆	★☆☆☆	★☆☆☆
Forecast skill	★★☆☆	★★★★	★★★☆
Calibration	★★★★	★★★☆	★★★★
Realistic images	★★★☆	★★★☆	★★★★
Realistic videos[1]	★★★☆	★★★☆	★★★☆
Data efficiency	★★★☆	★★★☆	★★☆☆

★ raw model output
★★ model output with ECC

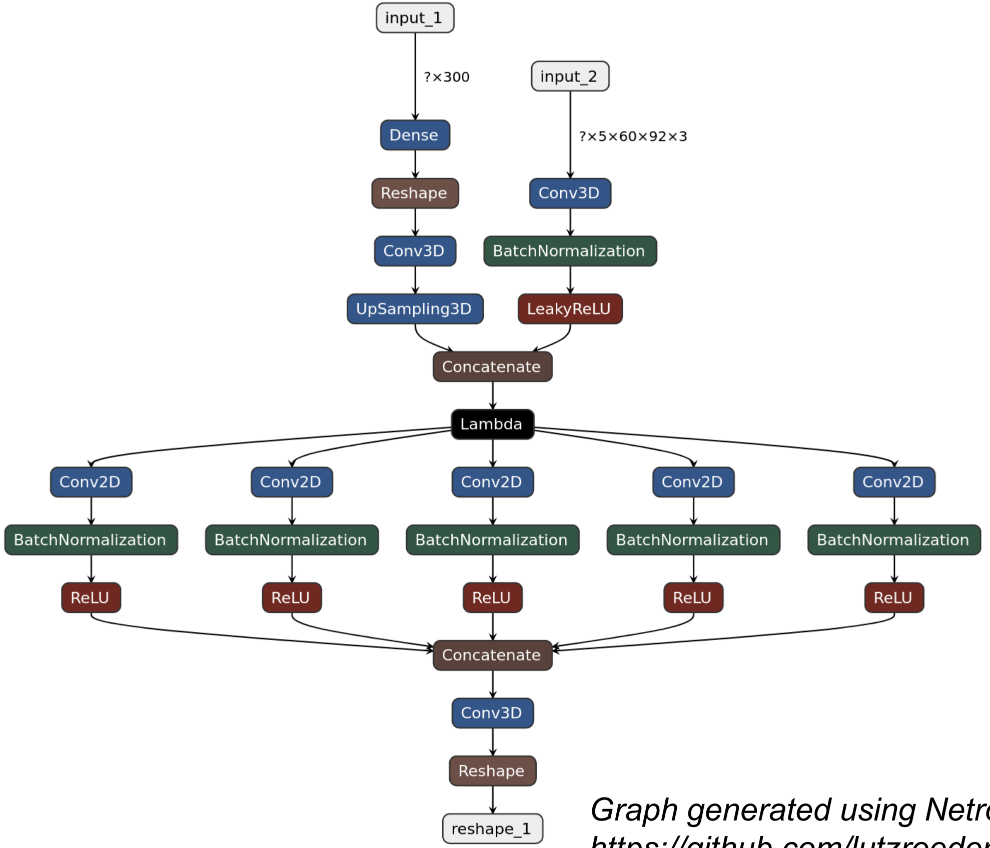
[1]temporal consistency provided by ECC

cGAN for precipitation

- Is cGAN model for cloud cover transferable to precipitation?
- Is it possible to include temporal dependence?
- Issues with skewness of precipitation
- Work with daily precipitation accumulations to simplify the problem
- Not transforming the data at all leads to ‘most realistic’ cGAN samples
  - Trade-off: training works only for simple generator architecture

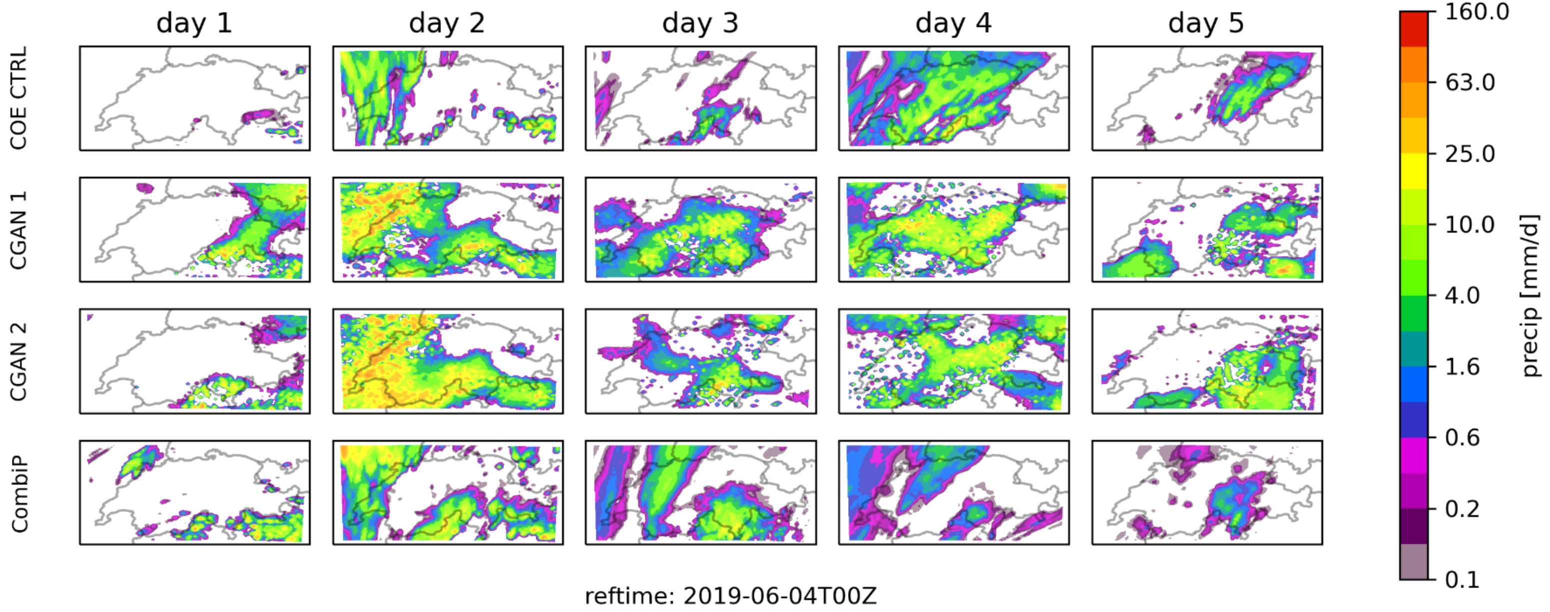
Generator architecture

- 11th, 16th, and 21th member of ordered and spatially smoothed COSMO-E used as features
- no compression of features
- Temporal split and lead day dependent 2D convolutions

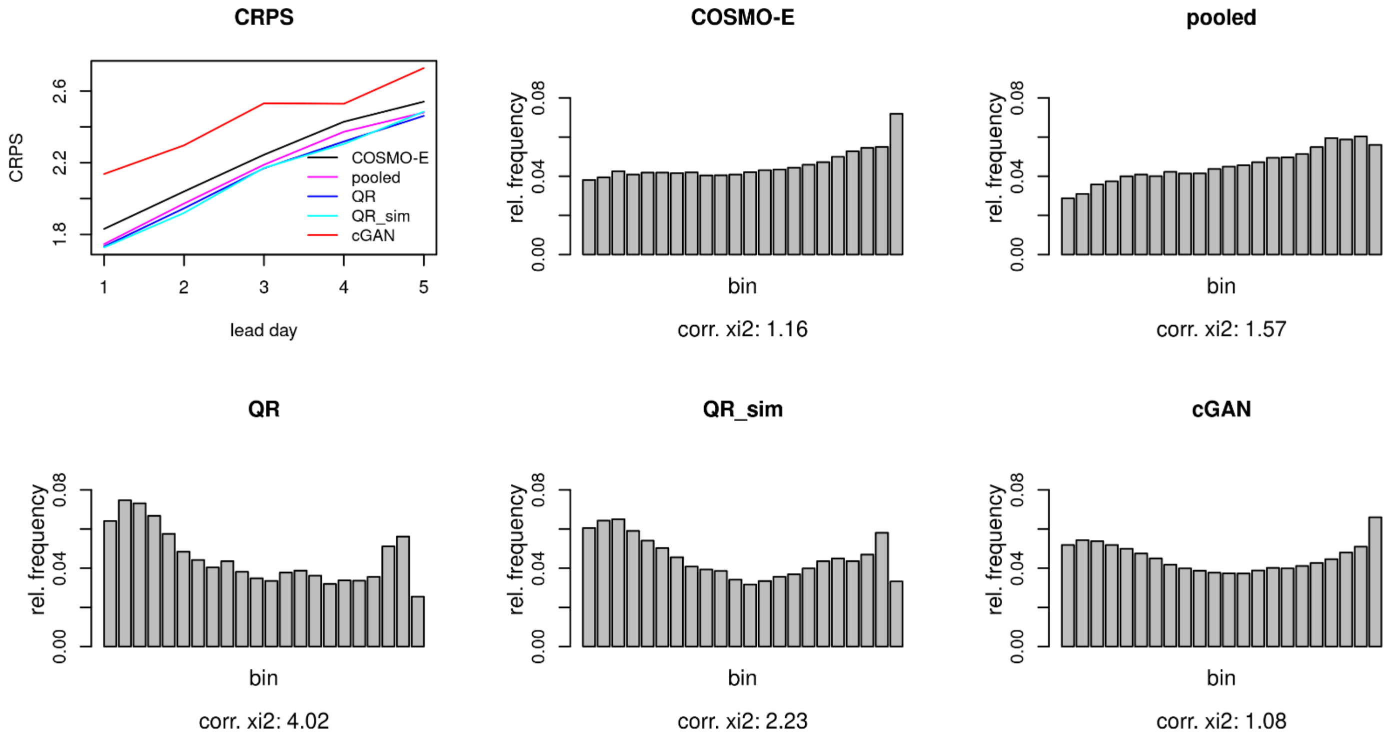


Graph generated using Netron
https://github.com/lutzroeder/Netron

Example forecasts

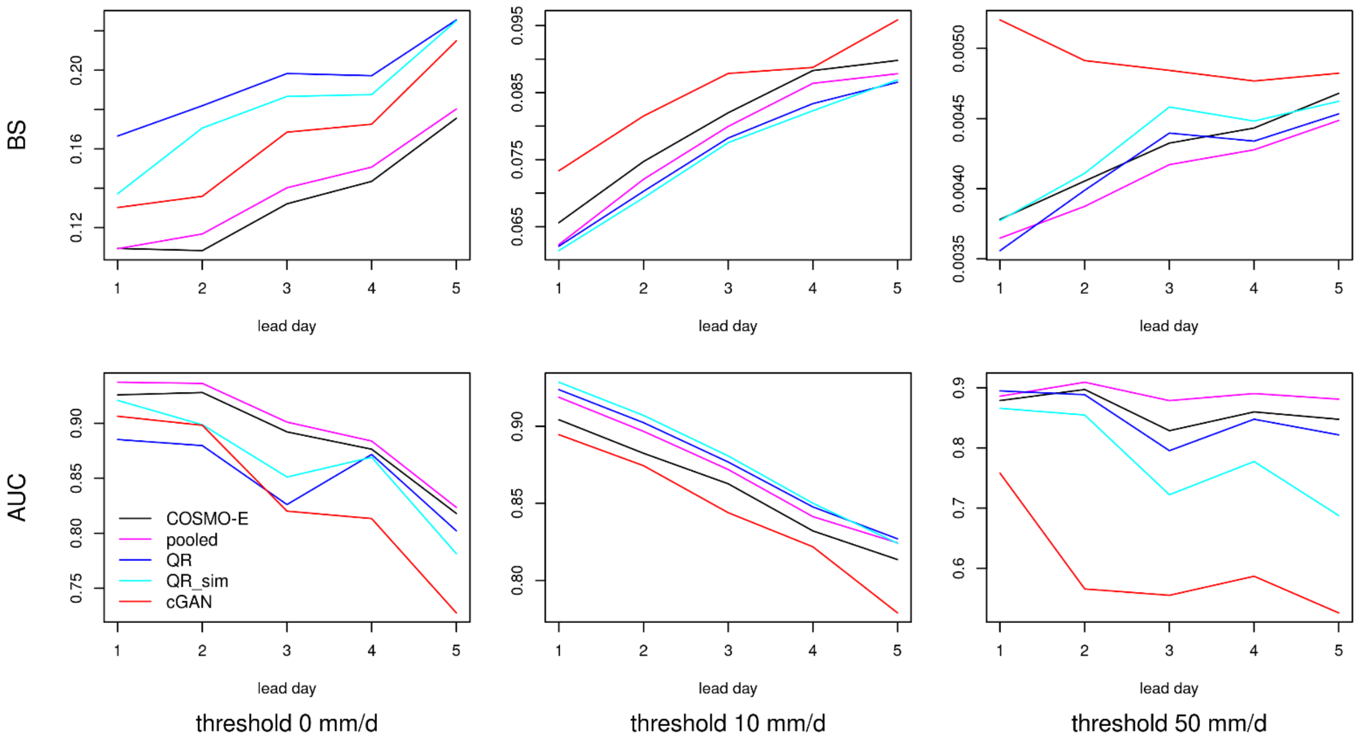


CRPS and calibration



- rank histograms for lead day 3
- pooled: simple spatial pooling
- QR: quantile regression
- QR_sim: similiarity / analog based QR

Brier score and AUC



Summary part 2

- cGAN generates quite realistic looking precipitation fields
- cGAN skill in terms of CRPS is poor
- cGAN produces comparatively well calibrated forecasts
- cGAN resolution probably poor, issues with conditioning on features
- Probably, there is still a lot of room for improvement