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Postprocessing of gridded precipitation forecasts using conditional generative adversarial networks and quantile regression

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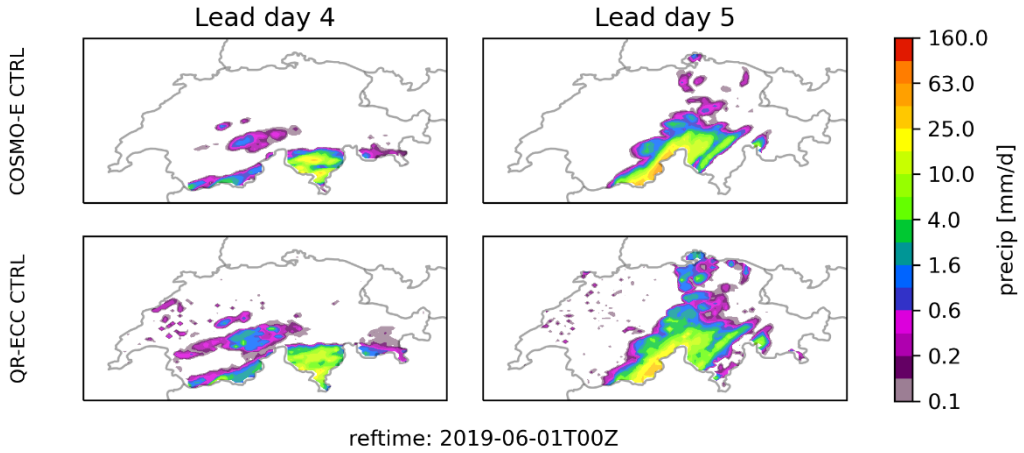
Motivation



- Quantile regression
- Ensemble copula coupling (ECC, Schefzik et al. 2013)
- Assumes realistic COSMO-E spatio-(temporal) dependence structure
- Artifacts[1]

[1]There exist ad-hoc methods to correct spatial ECC artifacts (Scheuerer and Hamill, 2018)

Motivation

Goals

- Spatio-temporal postprocessing of precipitation
- Realistic looking scenarios / maps
- No need for a spatio-temporal dependence template

Method:

- Conditional GAN (Mirza & Osindero, 2014) with content loss similar to Harris et al. (2022)

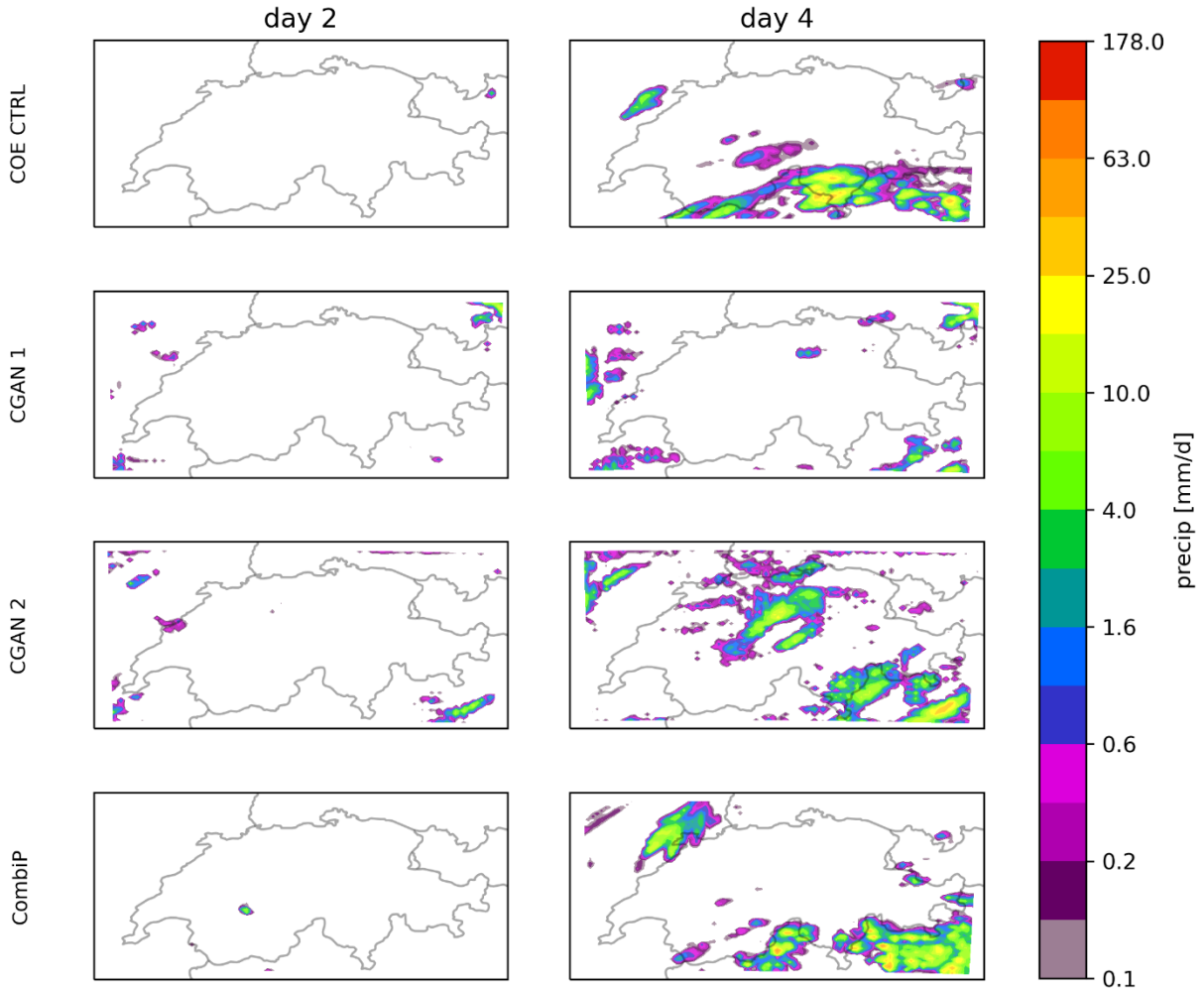
Data and methods I

- Features: COSMO-E 21 member high-resolution (2 km) DMO
- Labels: CombiPrecip gridded precipitation data
  - 1 km spatial resolution; 24h temporal resolution
  - blend of gauge observations with radar data
- Focus on JJAs
  - training set: 2014-2018
  - validation set: 2019
  - test set: 2020
- Reference method: quantile regression + ECC
- Work in progress, hence results shown only for validation set

Data and methods II – cGAN details

- Iterative training of generator and discriminator convolutional networks
  - generator tries to *fool* the discriminator
- Currently COSMO-E precipitation based features only
- Separated (Castro et al., 2021) 3D convolutions in generator and discriminator
- split network architectures along lead times/days in order to allow for lead time/day dependent weights
- add CRPS content loss inspired by Harris et al. (2022)

Example forecast



reftime: 2019-06-01T00Z

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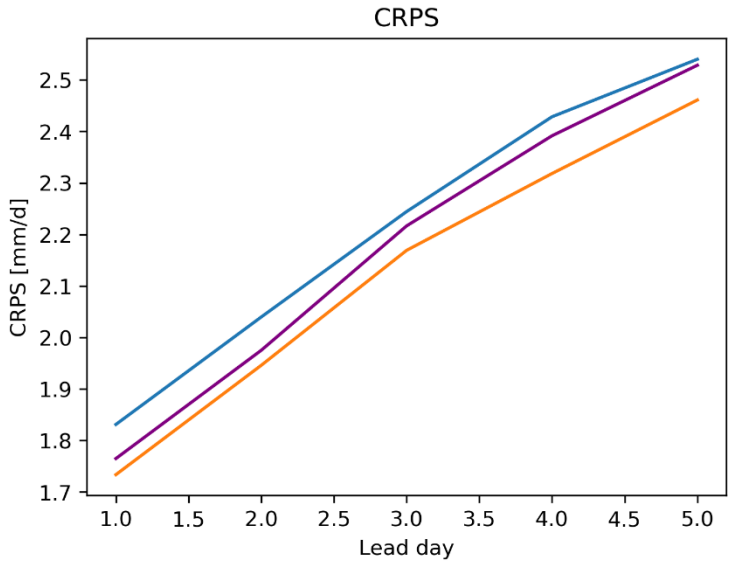
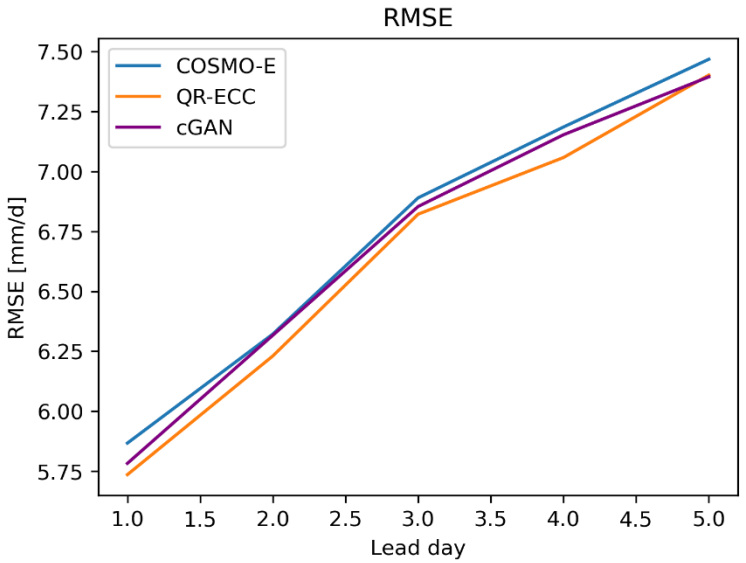
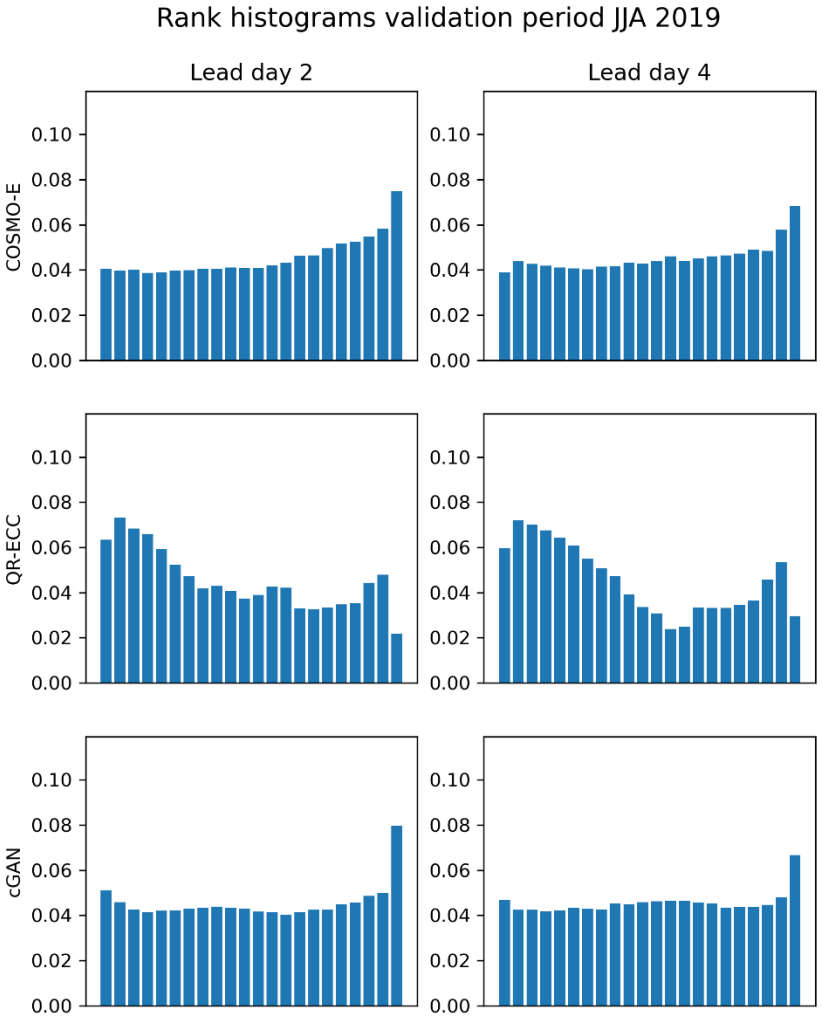
CRPS and RMSE





Calibration



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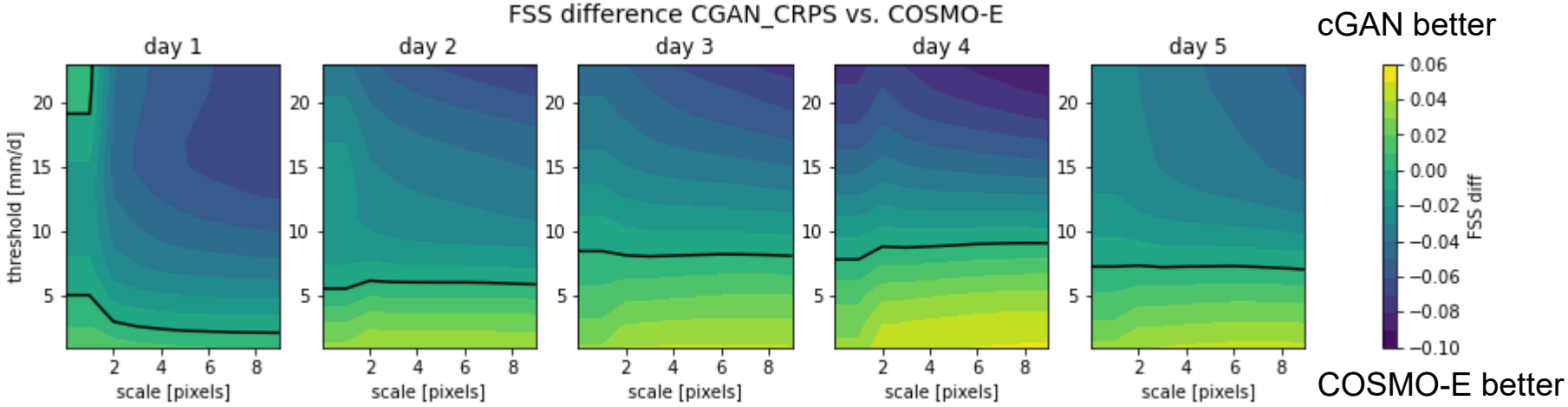
Fraction skill score difference



Multivariate verification

- Verify temporal and spatial dependence structure
- Energy score, multivariate generalization of the CRPS (Gneiting et al. 2007)
- p-variogram score, multivariate score focusing on differences in the empirical variograms (Scheuerer & Hamill, 2015)

Multivariate verification

	CRPS	ES-temp	ES-spat	P-temp	P-spat
COSMO-E	2.22	7.73	174.48	0.78	0.47
QR-ECC	2.13	7.49	171.04	0.74	0.46
cGAN	2.18	7.71	174.10	0.75	0.46

- QR-ECC and cGAN scores are equal or better than COSMO-E for all scores considered
- QR-ECC exhibits best scores
- cGAN comparable in terms of p-variogram score

Conclusions and outlook

- cGAN postprocessing of COSMO-E precipitation does work
- Univariate cGAN forecast skill comparable to COSMO-E skill
- QR-ECC still outperforms cGAN in terms of univariate forecast skill
- cGAN scenarios look quite realistic
- Multivariate verification of cGAN does not reveal any obvious flaws
- cGAN performs poorly for high thresholds
- Including additional features may improve cGAN forecast skill

References

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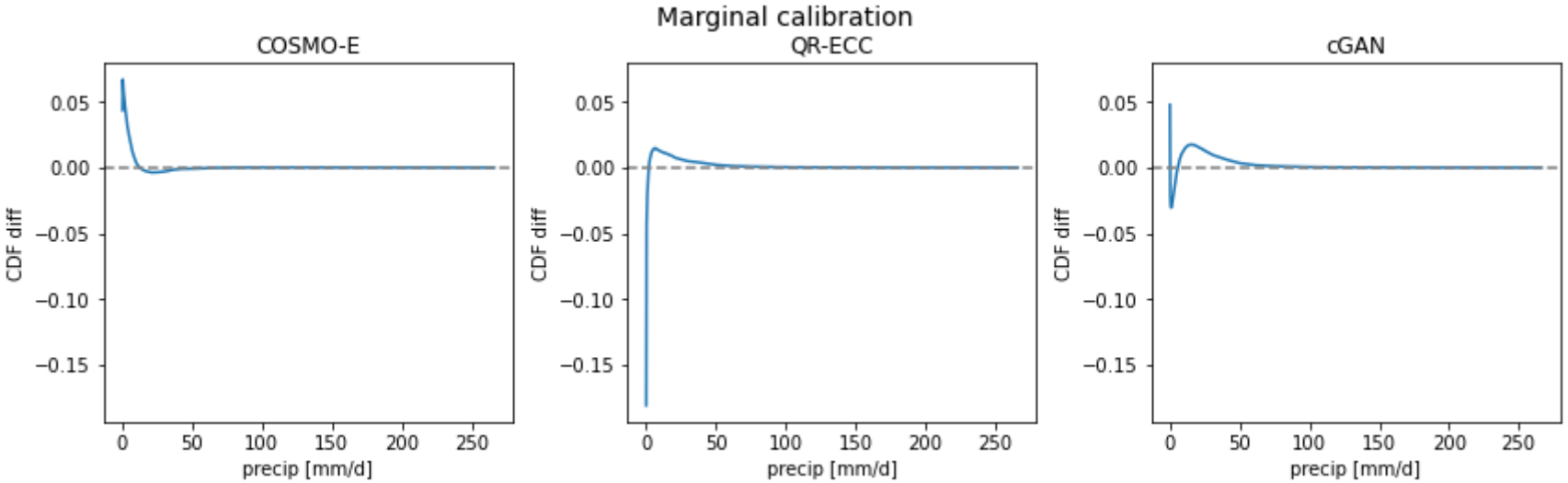
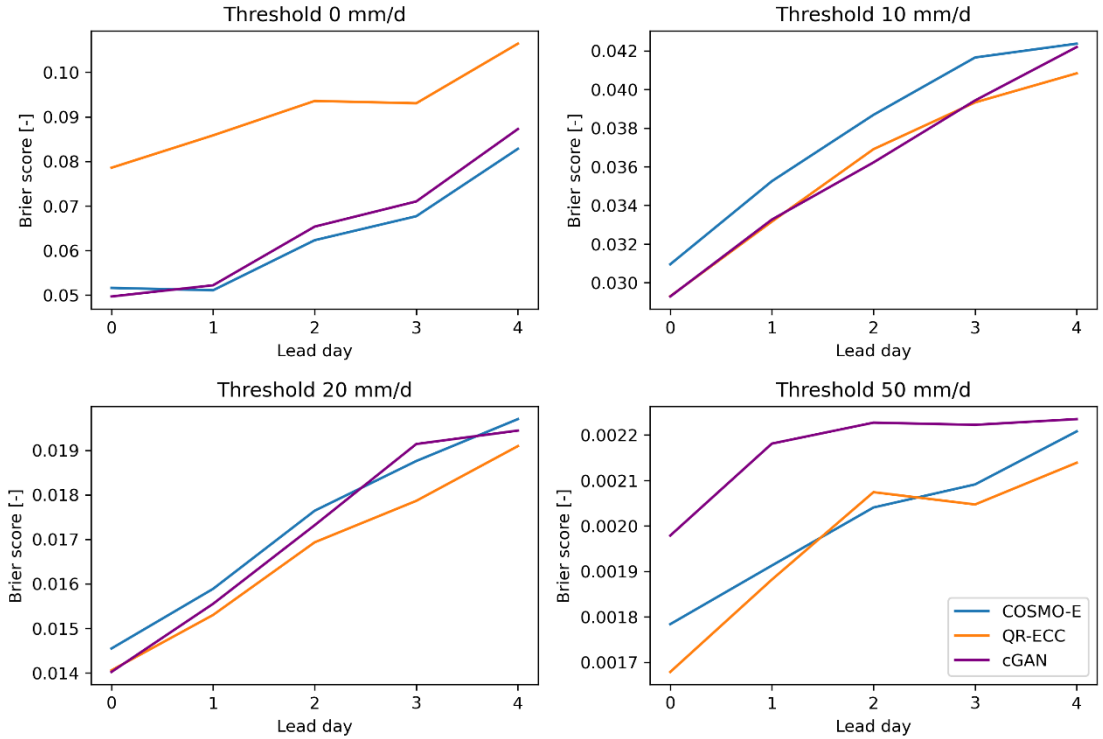
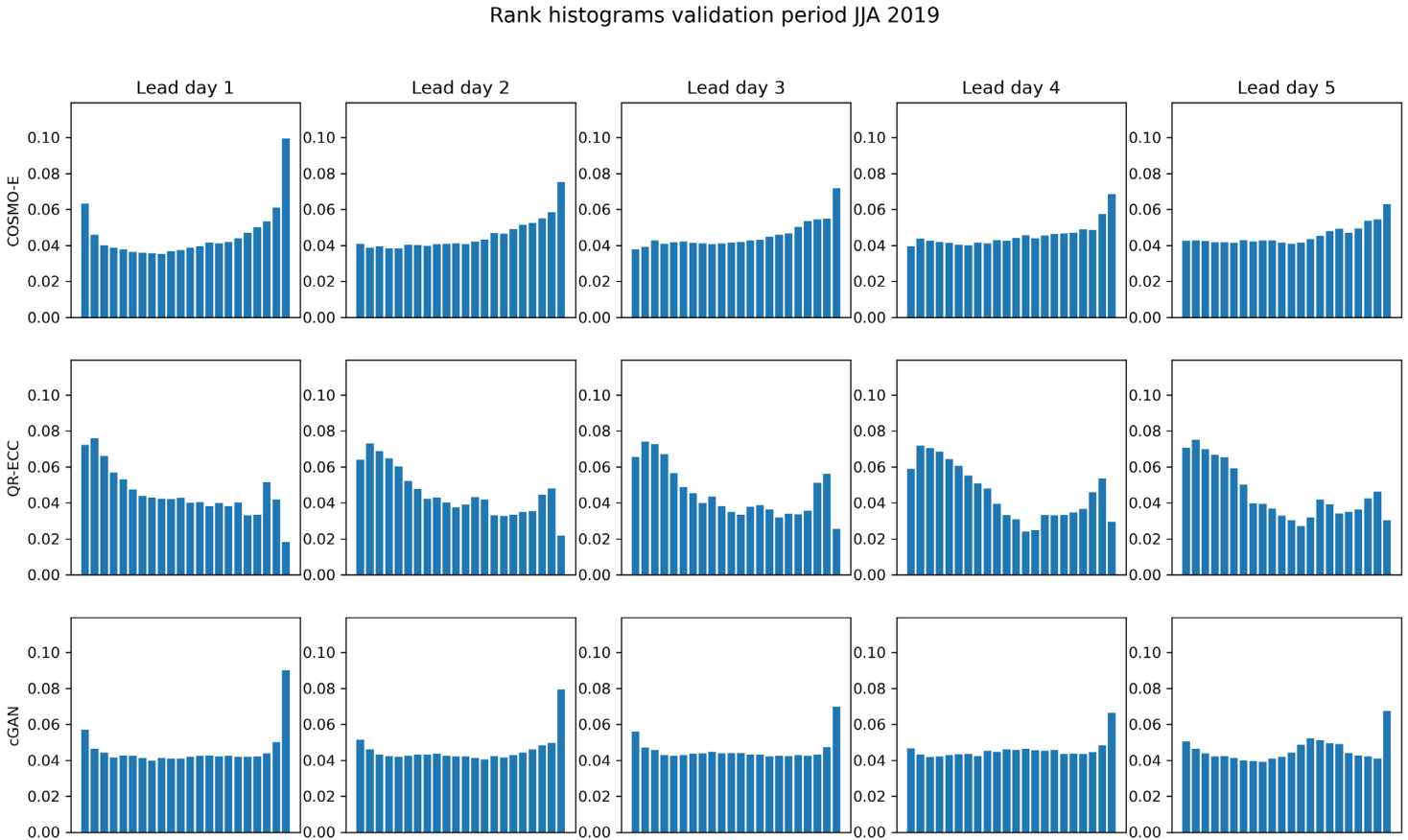
Supplementary material



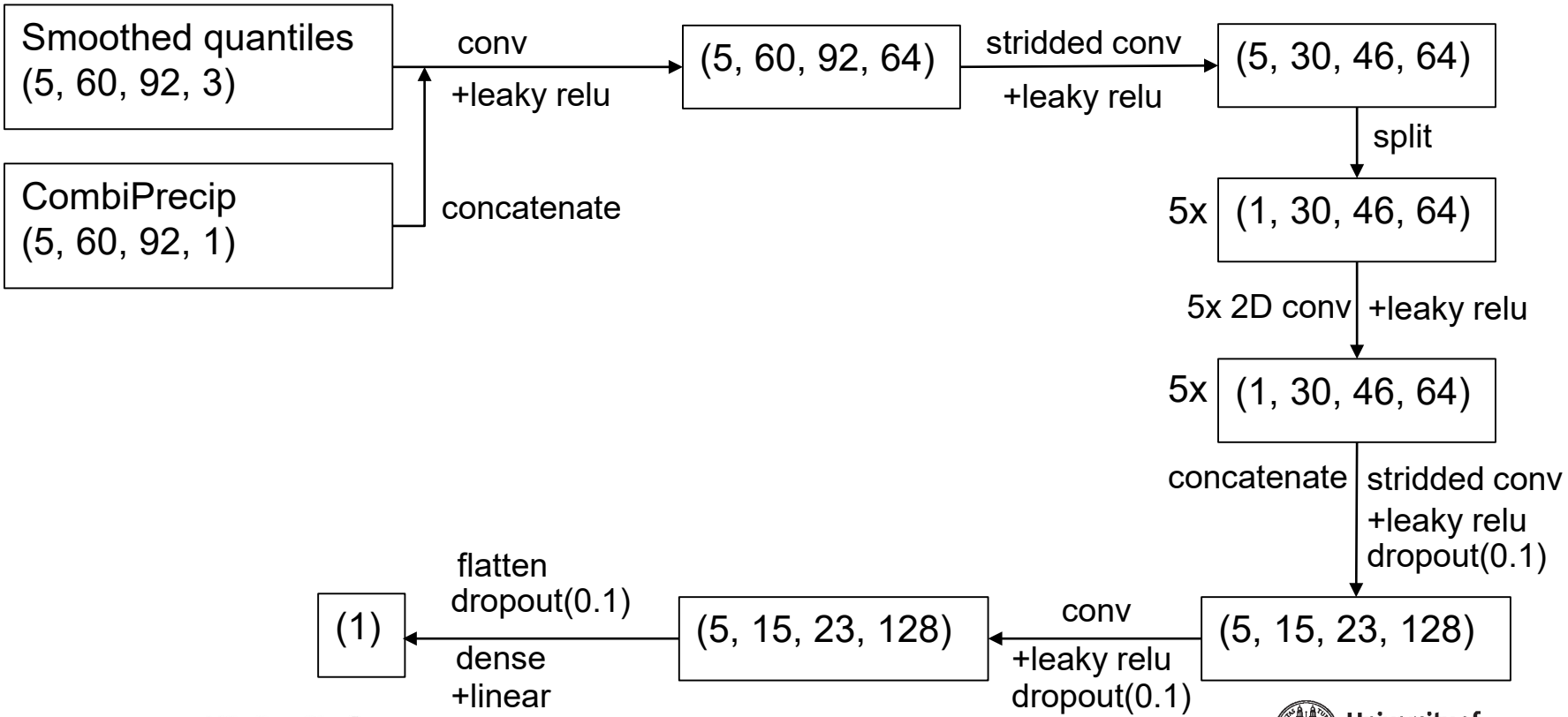
Brier scores



Calibration



cGAN discriminator architecture



cGAN generator architecture

