

# Machine Learning for (Multivariate) Downscaling

## A Generative Model Inspired by Forecast Evaluation

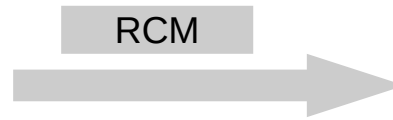
***Maybritt Schillinger, PhD @ETH Zurich***

*Joint work with Xinwei Shen, Maxim Samarin & Nicolai Meinshausen*

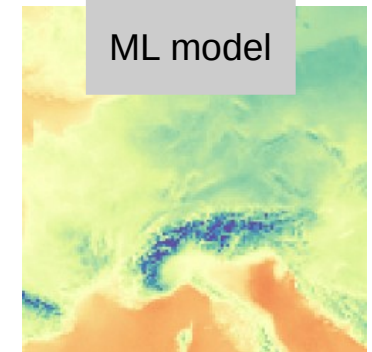
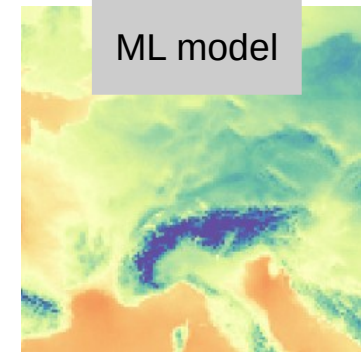
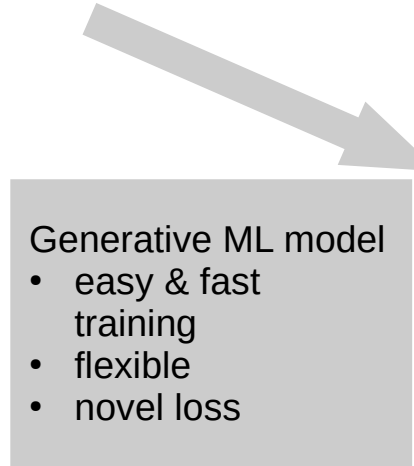
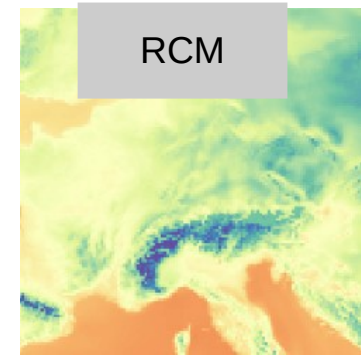
EGU24

# Goal: generative ML for CORDEX data

Low-res. **GCM** input



High-res. **RCM** output



# Goal: generative ML for CORDEX data

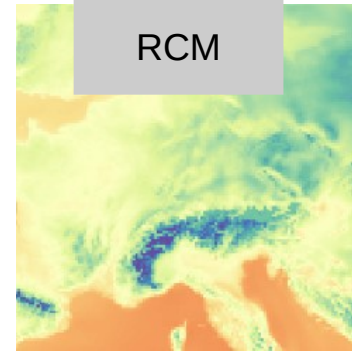
Low-res. **GCM** input



RCM

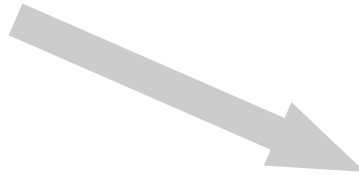


High-res. **RCM** output

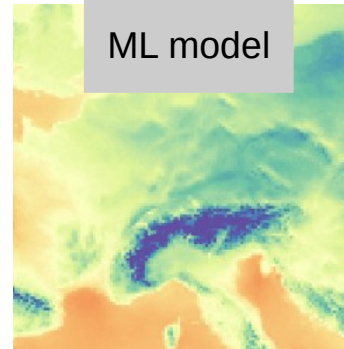


RCM

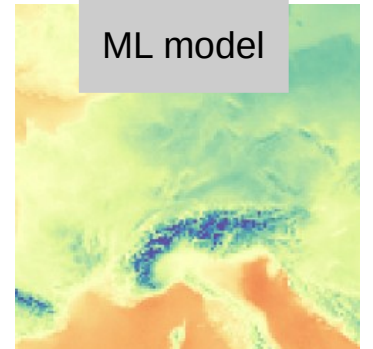
Generative ML model



ML model



ML model

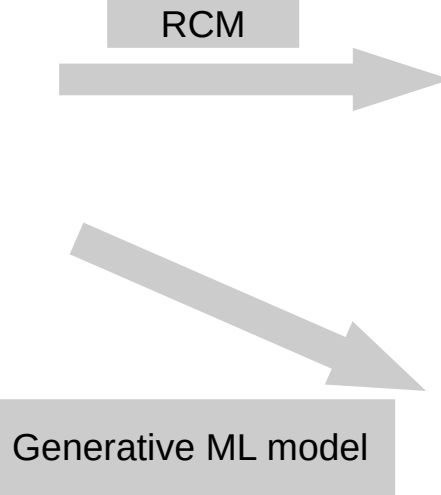
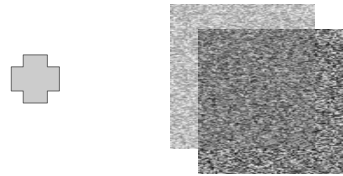
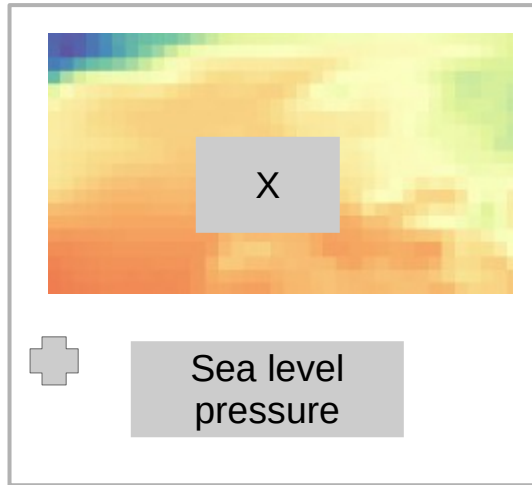


## Data

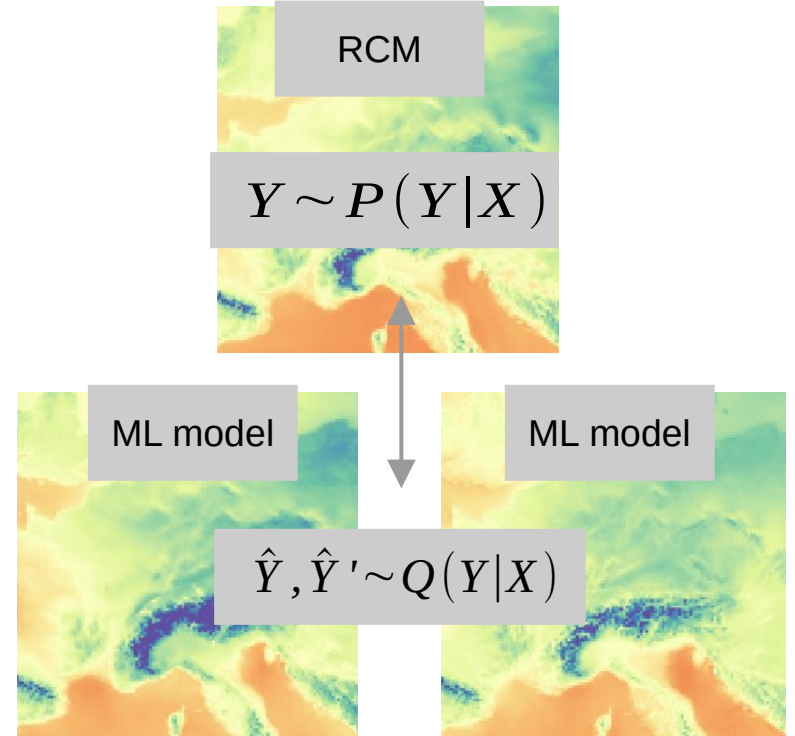
- 8 GCM-RCM pairs from EURO-CORDEX
- Daily data for years 1971-2099 (RCP 8.5)
- Tas & pr

# Goal: generative ML for CORDEX data

Low-res. **GCM** input



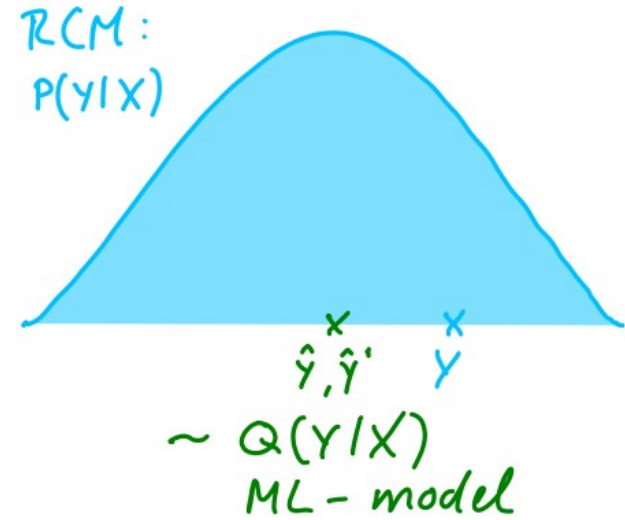
High-res. **RCM** output



# ML model: loss function & architecture

$$\text{Loss} = E[\|Y - \hat{Y}\|]$$

Prediction  
error



# ML model: loss function & architecture

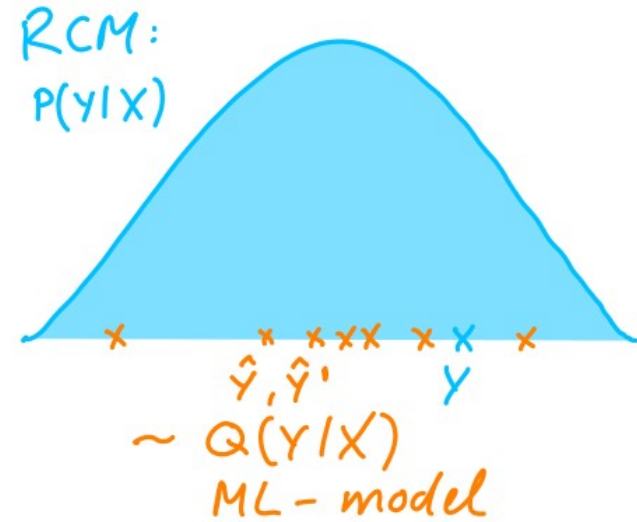
$$\text{Loss} = E[\|Y - \hat{Y}\|] - \frac{1}{2} E[\|\hat{Y} - \hat{Y}'\|]$$

Prediction  
error

Variability

Energy Score  
(multivariate CRPS)

**Theorem:**  
ES is minimal iff  $P = Q$ .



References: Gneiting 2007,  
Pacchiardi 2022

# ML model: loss function & architecture

$$\text{Loss} = E[||Y - \hat{Y}||] - \frac{1}{2} E[||\hat{Y} - \hat{Y}'||]$$

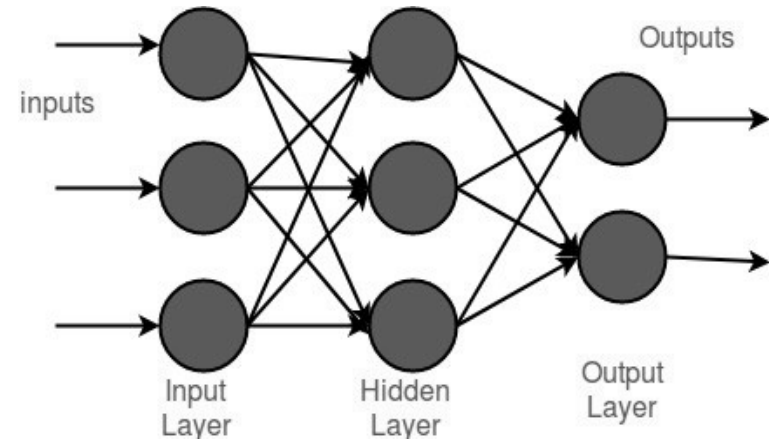
Prediction  
error

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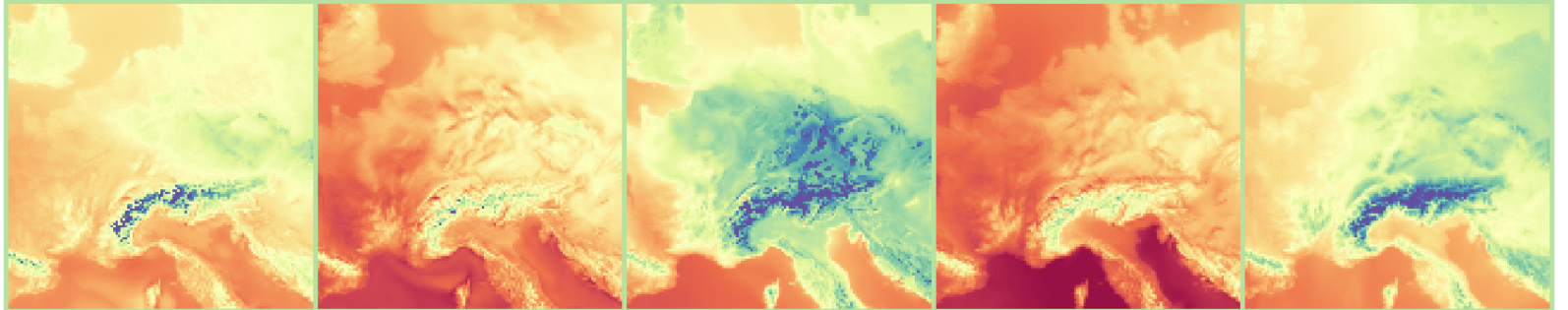
## Architecture



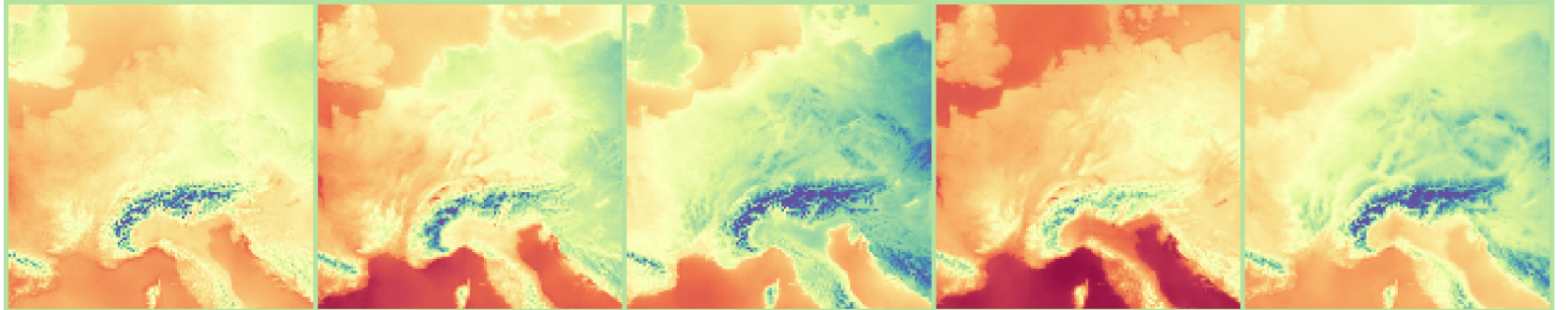
<https://www.geeksforgeeks.org/multi-layer-perceptron-learning-in-tensorflow/>

# Results: realistic generated images (tas)

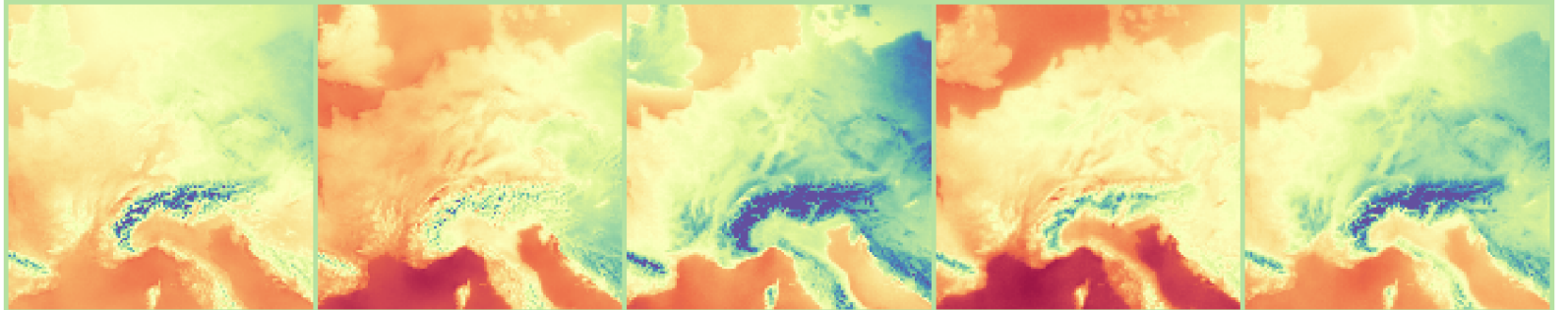
RCM



Sample1

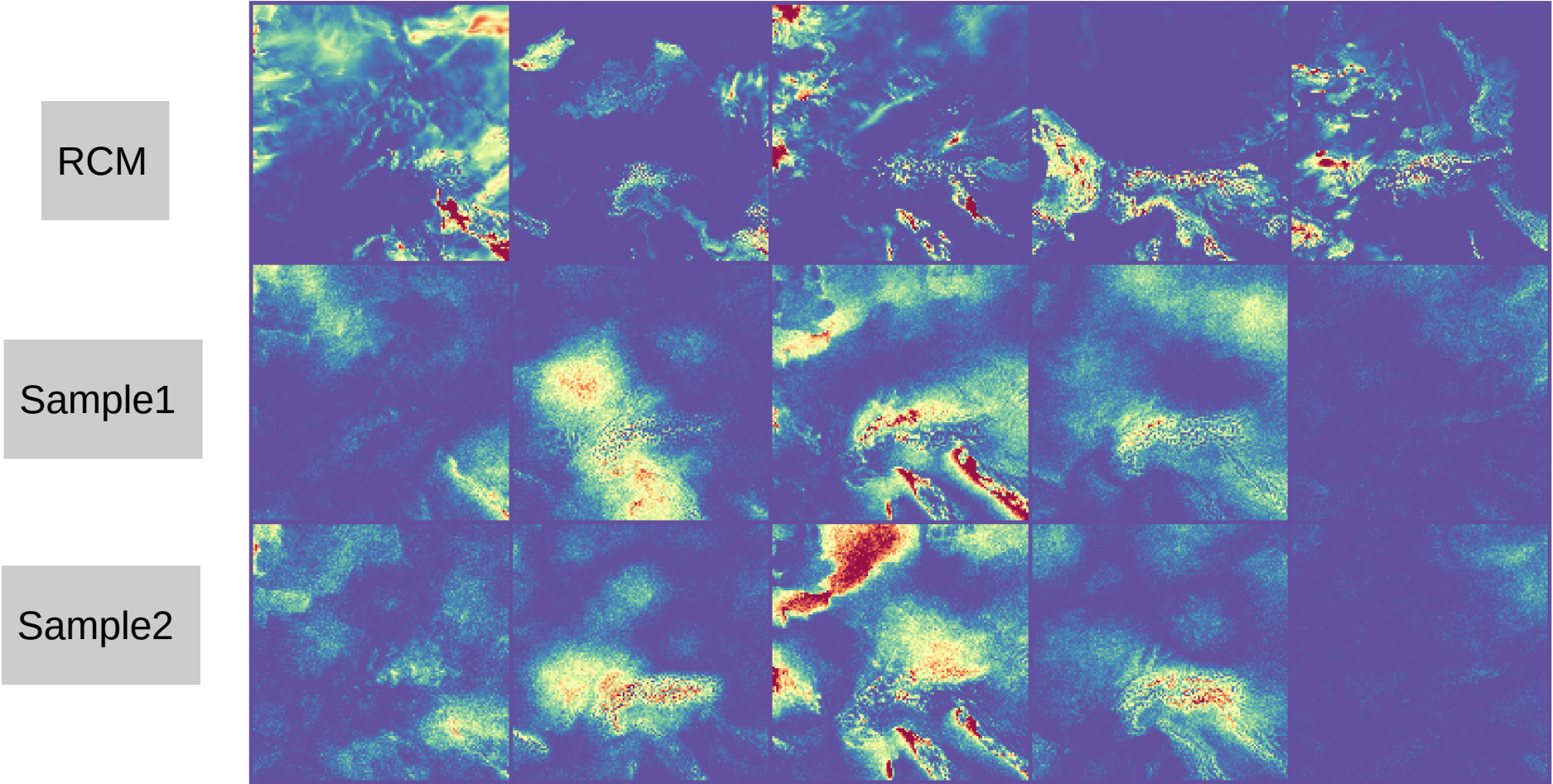


Sample2





# Results: realistic generated images (pr)



# Benchmarks and evaluation metrics

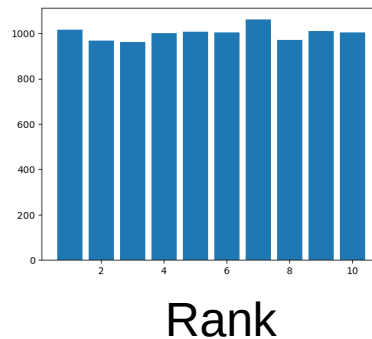
## Benchmarks

- Analogues
- Linear Model
- Linear Model + EasyUQ

## Metrics

- Energy score
- Quantiles
- Rank histograms
- ...

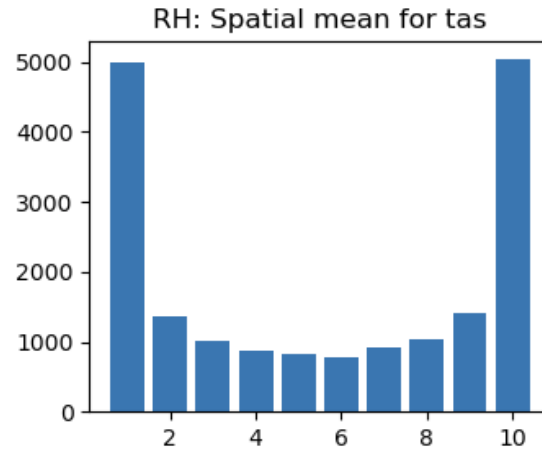
**Flat:**  
**Correct variability**



# Evaluation summary



- Too little variability (overfitting!)



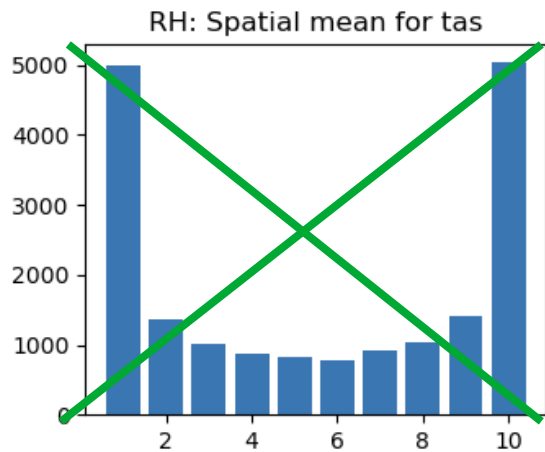
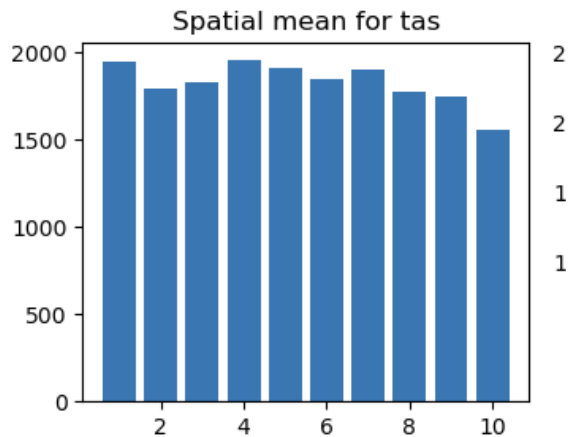
# Evaluation summary



- ~~Spatial structure good~~
- Correct variability



- ~~Too little variability (overfitting!)~~
- Worse spatial structure



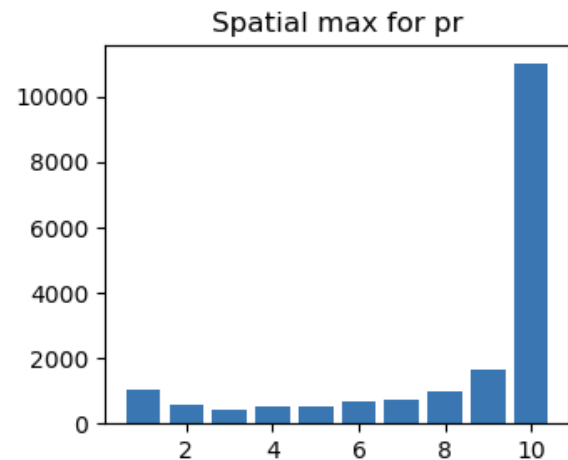
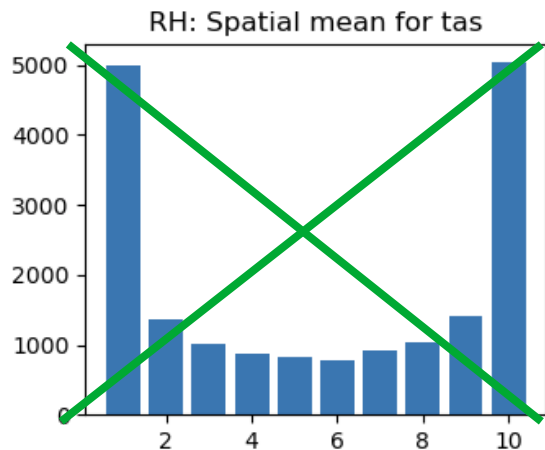
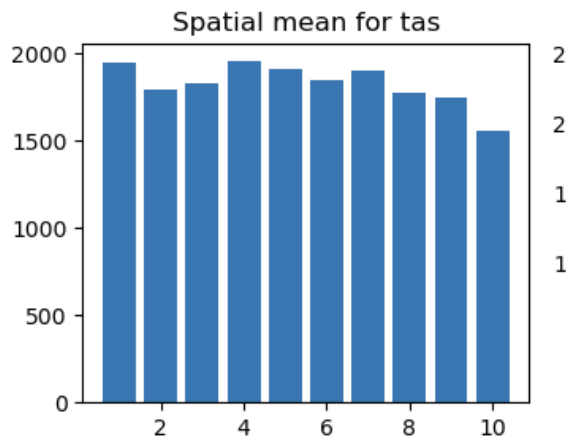
# Evaluation summary



- ~~Spatial structure good~~
- Correct variability



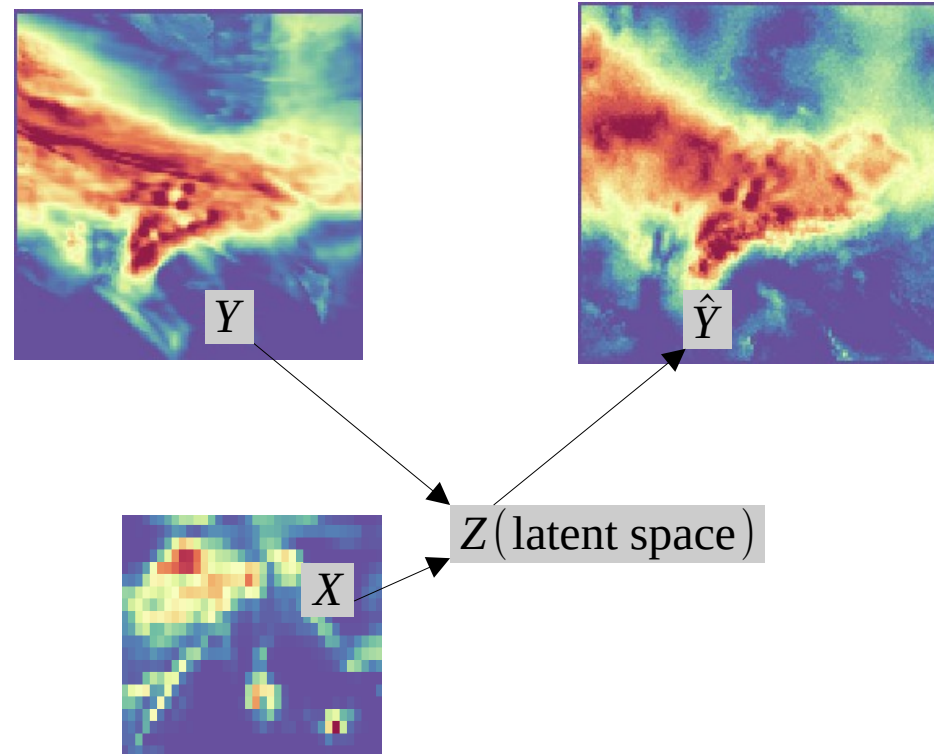
- ~~Too little variability (overfitting!)~~
- Worse spatial structure
- Underestimate high precipitation



# Work in progress: dimension reduction

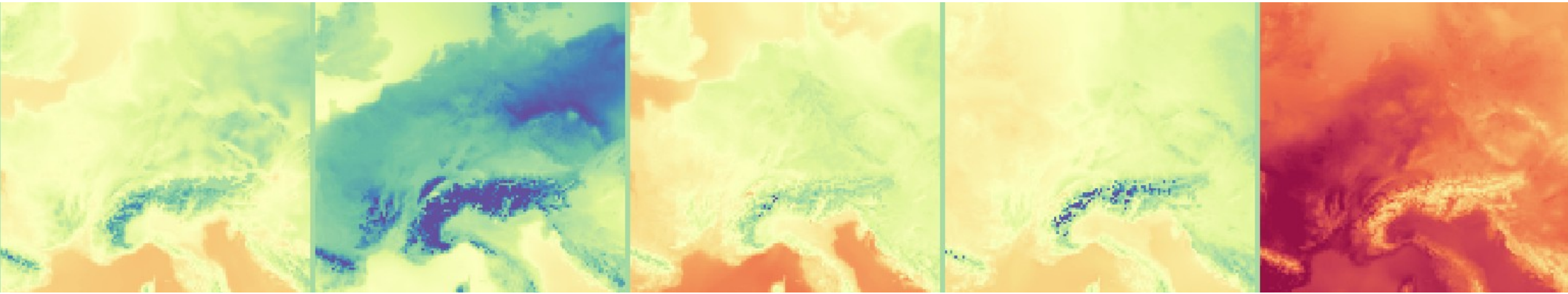
- Multivariate downscaling
- Bias-correction to observational data

## Dimension reduction



# Take Home Messages

1. Generative models with scoring rules are an easy-to-use and flexible tool.
2. Open questions, e.g. around multivariate versions and bias-correction.
3. Current results for downscaling seem promising.



Thank you! Questions? Feedback?

# Appendix



# References

## Data

EURO-CORDEX Community, 2016: EURO-CORDEX simulation list, maintained by H. Truhetz (contact: heimo.truhetz@uni-graz.at); accessed 13.12.2016. <http://www.euro-cordex.net/imperia/md/content/csc/cordex/20160204a-eurocordex-simulations.pdf>

C. Spirig and E. Zubler (2016): New observational datasets: Documentation and recommendation; [https://wiki.c2sm.ethz.ch/pub/CH2018/WebHome/CH2018\\_obs\\_data.pdf](https://wiki.c2sm.ethz.ch/pub/CH2018/WebHome/CH2018_obs_data.pdf)

Jacob, D.; Petersen, J.; Eggert, B.; Alias, A.; Christensen, O. B.; Bouwer, L. M.; Braun, A.; Colette, A.; Déqué, M.; Georgievski, G.; Georgopoulou, E.; Gobiet, A.; Menut, L.; Nikulin, G.; Haensler, A.; Hempelmann, N.; Jones, C.; Keuler, K.; Kovats, S.; Kröner, N.; Kotlarski, S.; Kriegsman, A.; Martin, E.; van Meijgaard, E.; Moseley, C.; Pfeifer, S.; Preuschmann, S.; Radermacher, C.; Radtke, K.; Rechid, D.; Rounsevell, M.; Samuelsson, P.; Somot, S.; Soussana, J.-F.; Teichmann, C.; Valentini, R.; Vautard, R.; Weber, B. & Yiou, P. EURO-CORDEX (2014): new high-resolution climate change projections for European impact research Regional Environmental Changes. Vol. 14, Issue 2, pp. 563-578., <https://doi.org/10.1007/s10113-013-0499-2>

# References

## General

Jieyu Chen, Sebastian Lerch, and Tim Janke. “Generative machine learning methods for multivariate ensemble post-processing”. In: EGU General Assembly 2022, Vienna, Austria, 23–27 May 2022 MI (2022). url: <https://lens.org/189-140-183-158-58X>.

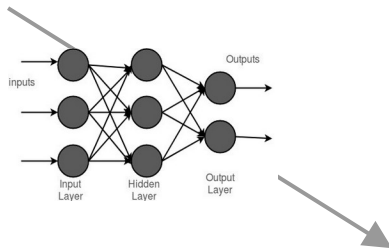
Tilmann Gneiting and Adrian E. Raftery. “Strictly proper scoring rules, prediction, and estimation”. In: Journal of the American Statistical Association 102.477 (2007), pp. 359–378. issn: 01621459. doi: 10.1198/016214506000001437.

Lorenzo Pacchiardi et al. “Probabilistic Forecasting with Generative Networks via Scoring Rule Minimization”. In: (Dec. 2021). URL: <http://arxiv.org/abs/2112.08217>.

# Bias-correction: idea

$X$  (Low-res)  $\xrightarrow{\text{physical model}}$

$$Y_{RCM} \sim P_{RCM}(Y|X)$$



Minimise dist

$$Y_{Obs}, Y'_{Obs} \sim Q_{Obs}(Y|X)$$

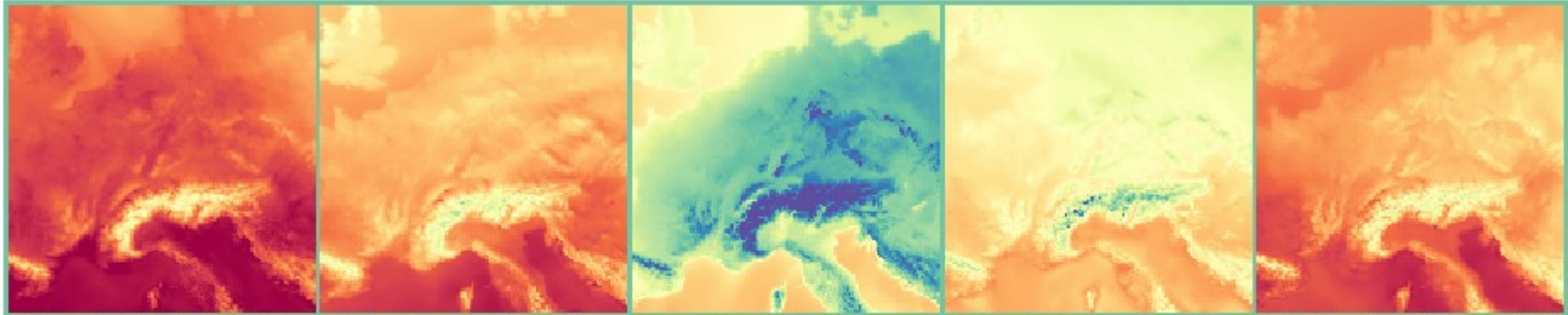
$Q_{Obs}(Y)$  should match marginal observational distribution  $P_{Obs}(Y)$

Idea:

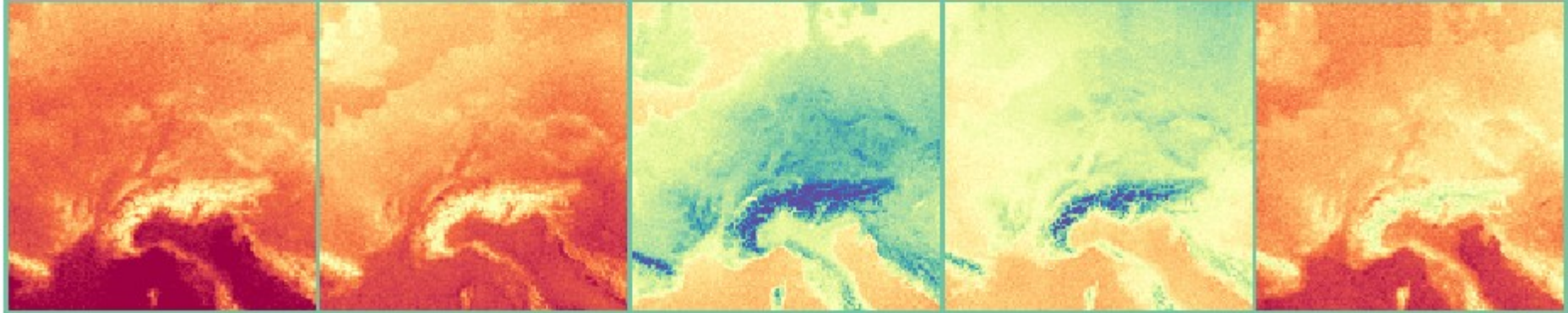
minimise  $ES(P_{RCM}(Y|X), Q_{Obs}(Y|X))$   
subject to:  $P_{Obs}(Y) = Q_{Obs}(Y)$

# Results: examples with other architecture (tas)

True



Gen.



# Results: examples with other architecture (pr)

Truth

Sample1

Sample2

