Generative Modelling for Multivariate Downscaling via Proper Scoring Rules

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Joint work with Xinwei Shen, Maxim Samarin & Nicolai Meinshausen

IMSC 2024

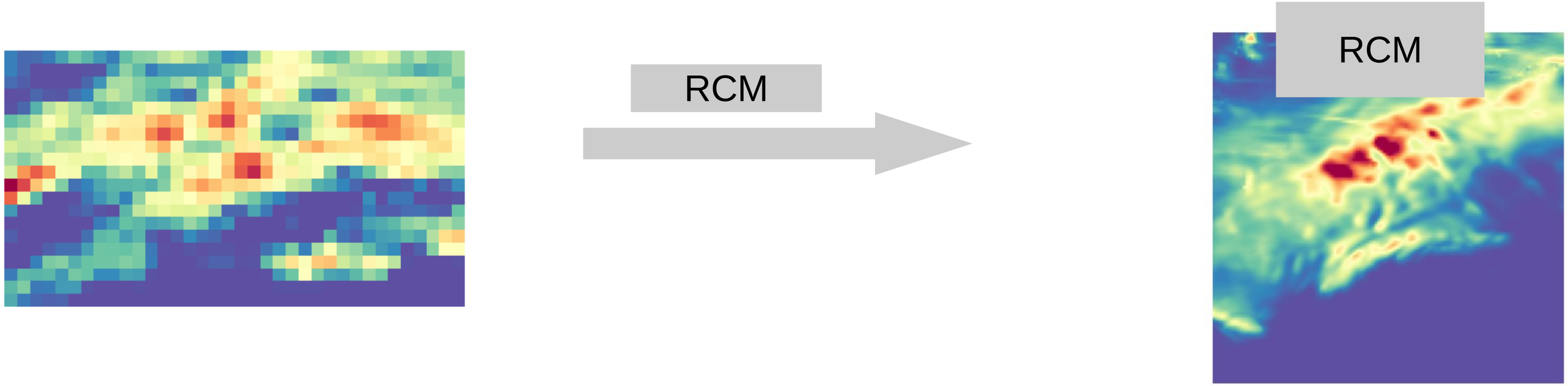
ETH zürich

SPEED2ZERO

Goal: generative ML for CORDEX data

Low-res. **GCM** input

High-res. **RCM** output



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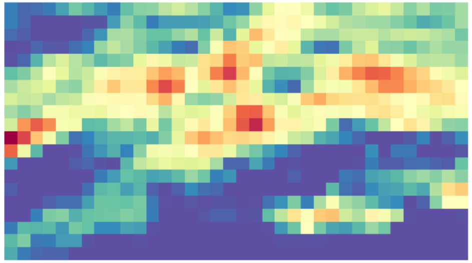
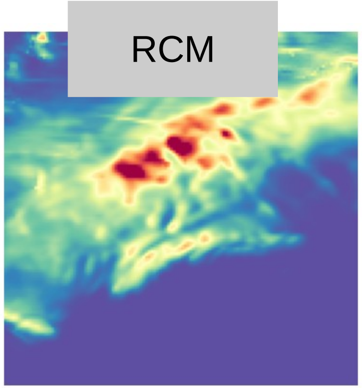
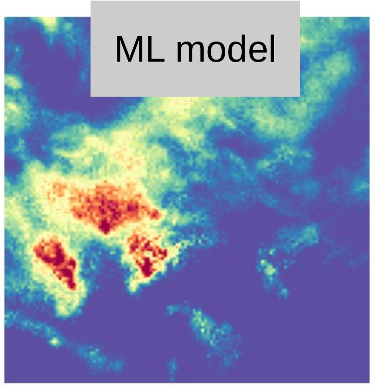
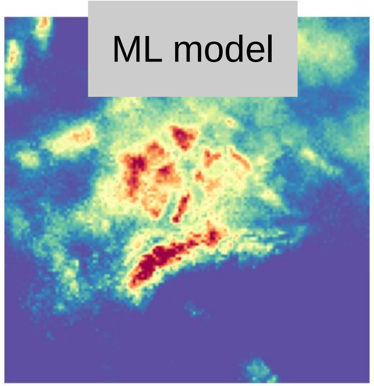


RCM



Generative ML model
- easy & fast training
- flexible
- novel loss





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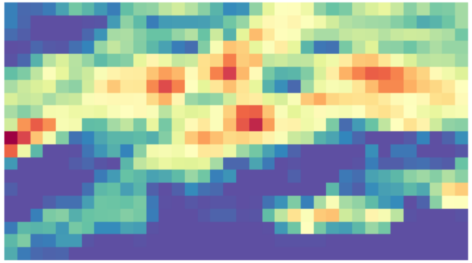
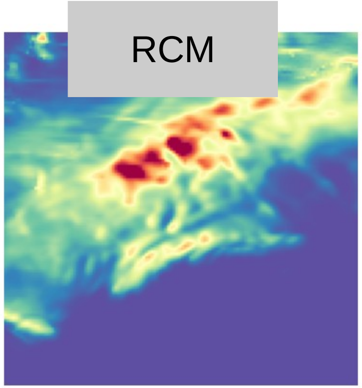
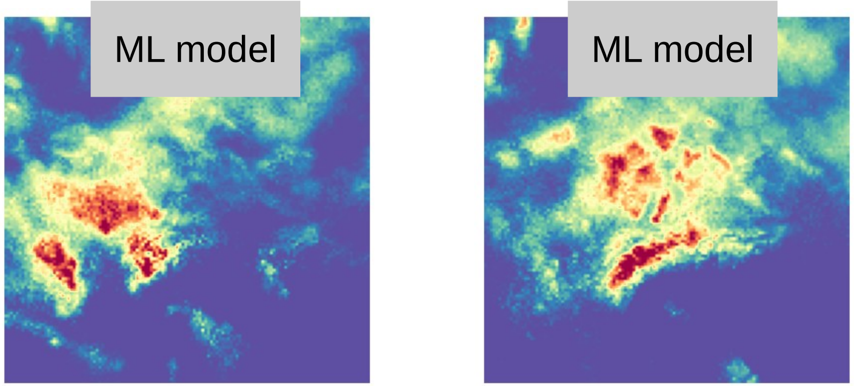


RCM

Generative ML model

High-res. **RCM** output





Data

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

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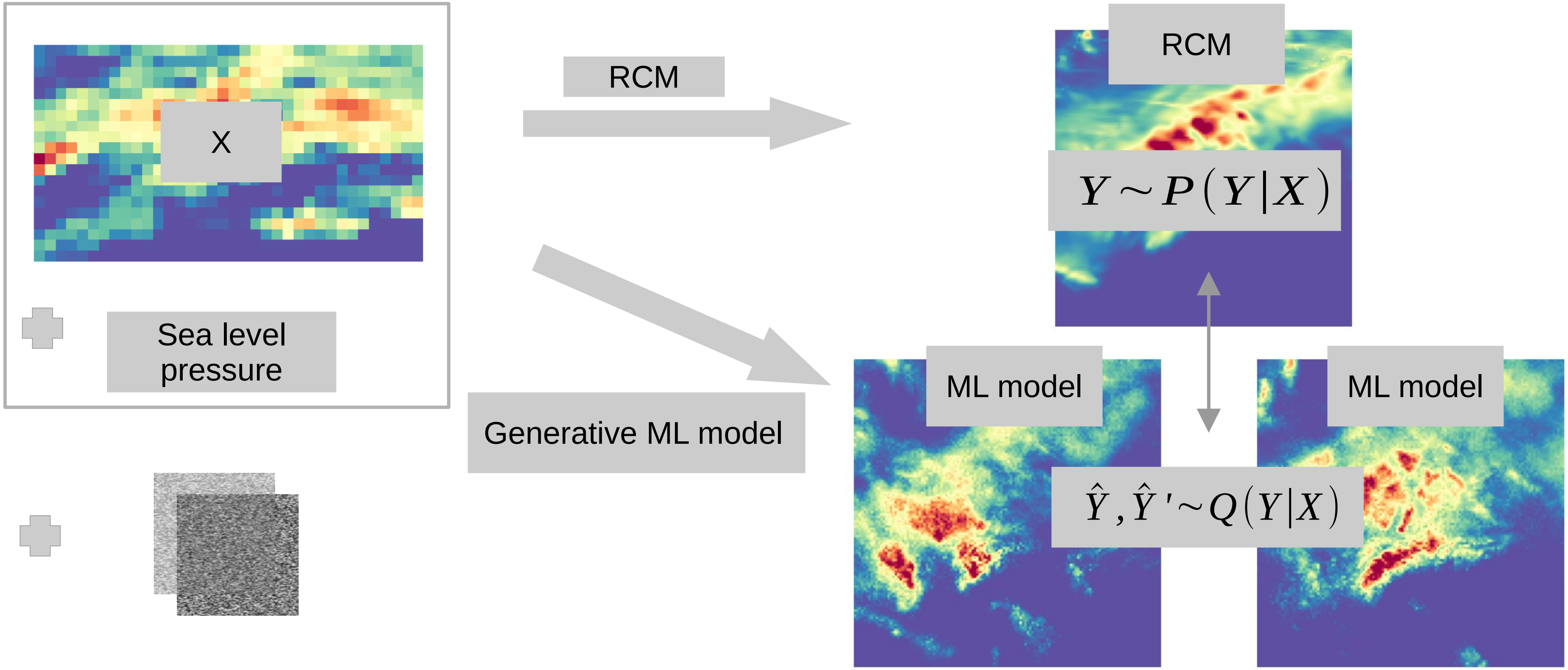
Low-res. **GCM** input

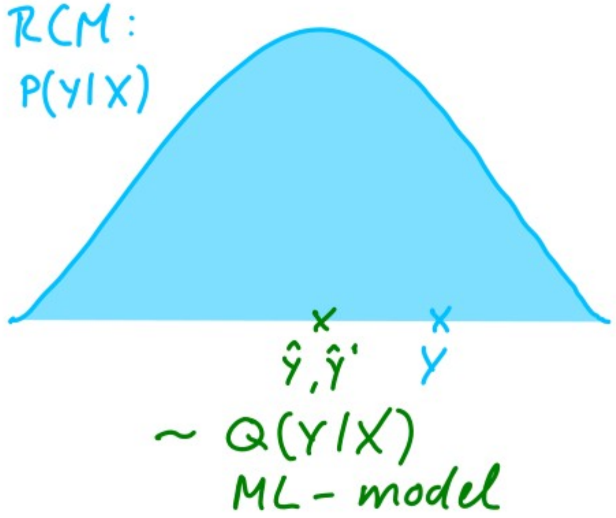
High-res. **RCM** output



ML model: loss function & architecture

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

Prediction error

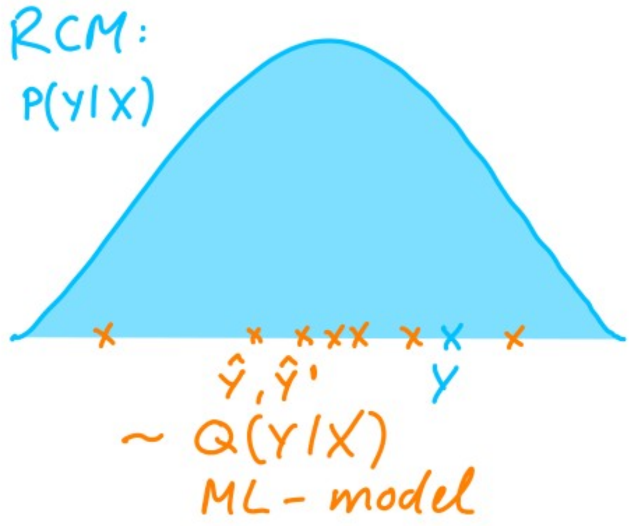


ML model: loss function & architecture

$$\text{Loss} = \underbrace{E[\|Y - \hat{Y}\|]}_{\text{Prediction error}} - \frac{1}{2} \underbrace{E[\|\hat{Y} - \hat{Y}'\|]}_{\text{Variability}}$$

Energy Score
(multivariate CRPS)

Theorem:
ES is minimal iff P = Q.



References: Gneitning 2007,
Pacchiardi 2022

ML model: loss function & architecture

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

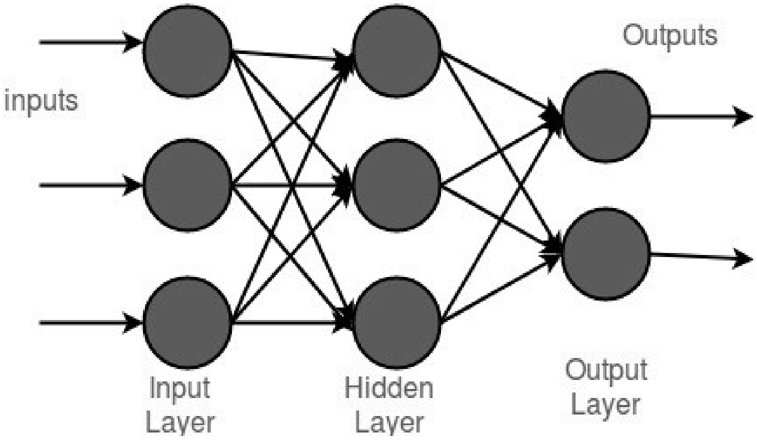
Prediction error

Variability

Energy Score
(multivariate CRPS)

Theorem:
ES is minimal iff P = Q.

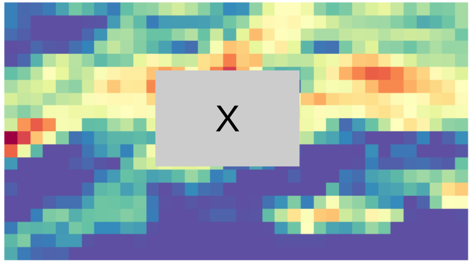
Architecture



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

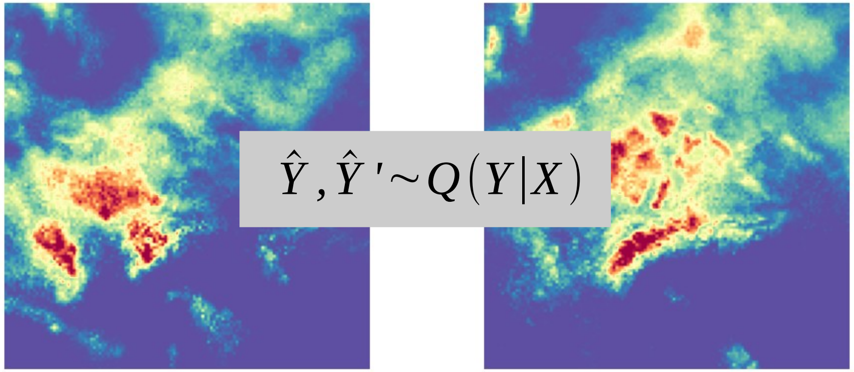
Direct prediction overfits

Low-res. **GCM** input



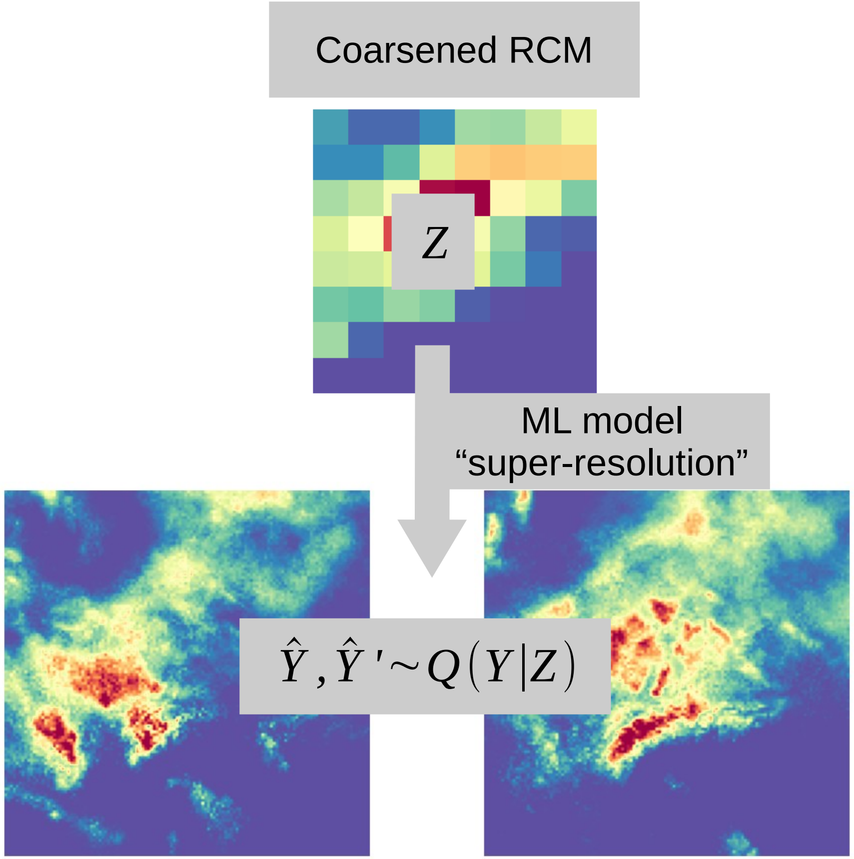
Problem:
Overfitting

Generative ML model

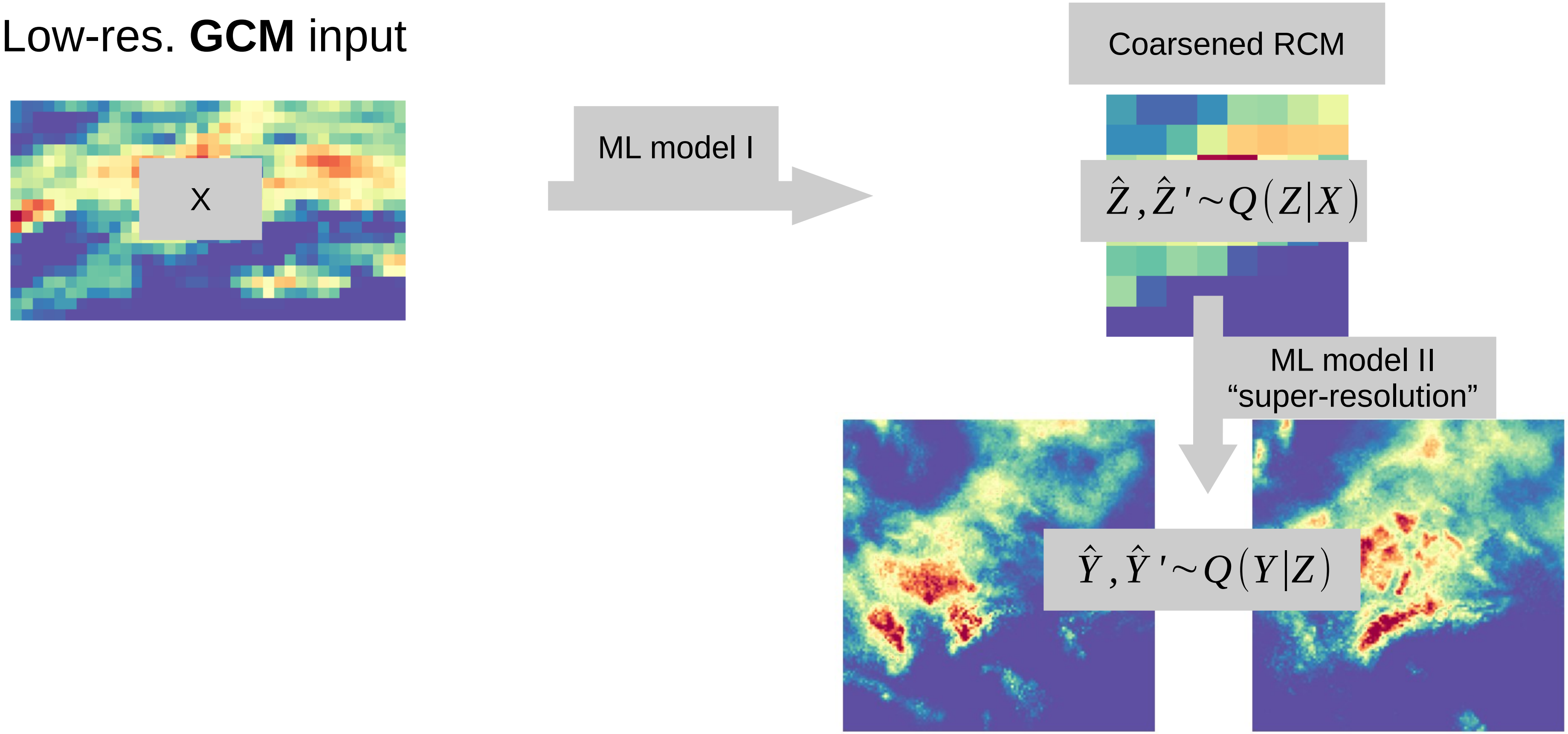


$$\hat{Y}, \hat{Y}' \sim Q(Y|X)$$

2-step approach alleviates overfitting



2-step approach alleviates overfitting



2-step approach alleviates overfitting

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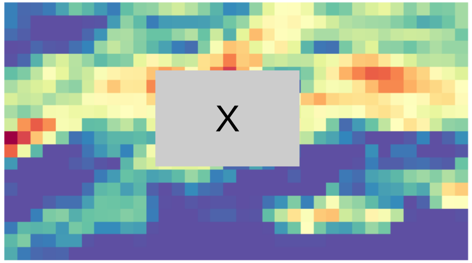
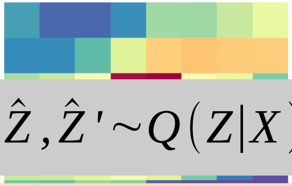


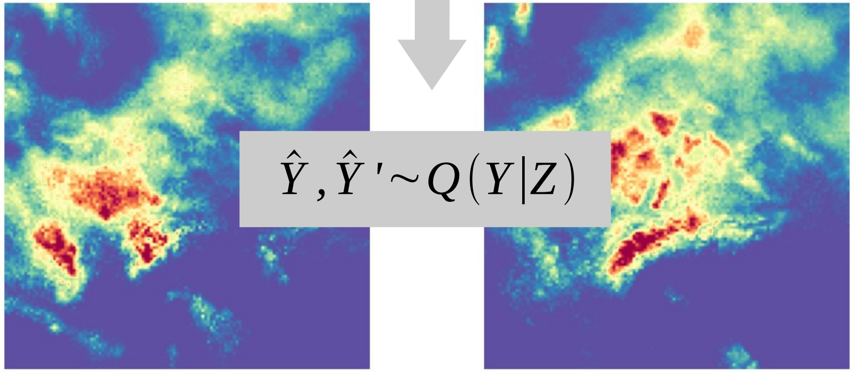
low-dimensional

Coarsened RCM



$\hat{Z}, \hat{Z}' \sim Q(Z|X)$

High-dimensional,
but data almost i.d.



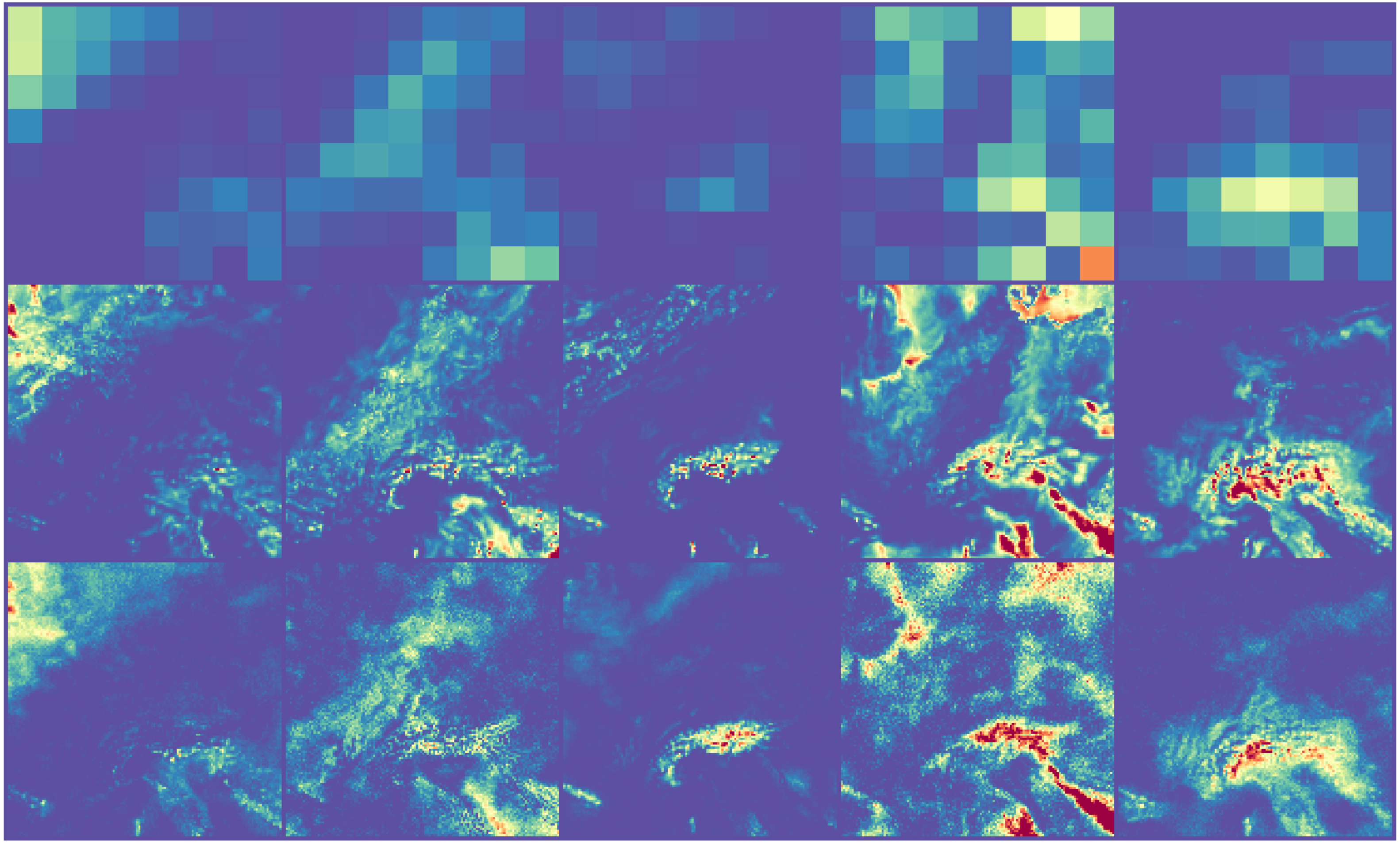
$\hat{Y}, \hat{Y}' \sim Q(Y|Z)$

Result: Super-resolution (pr)

Coarsened RCM

RCM

Sample1

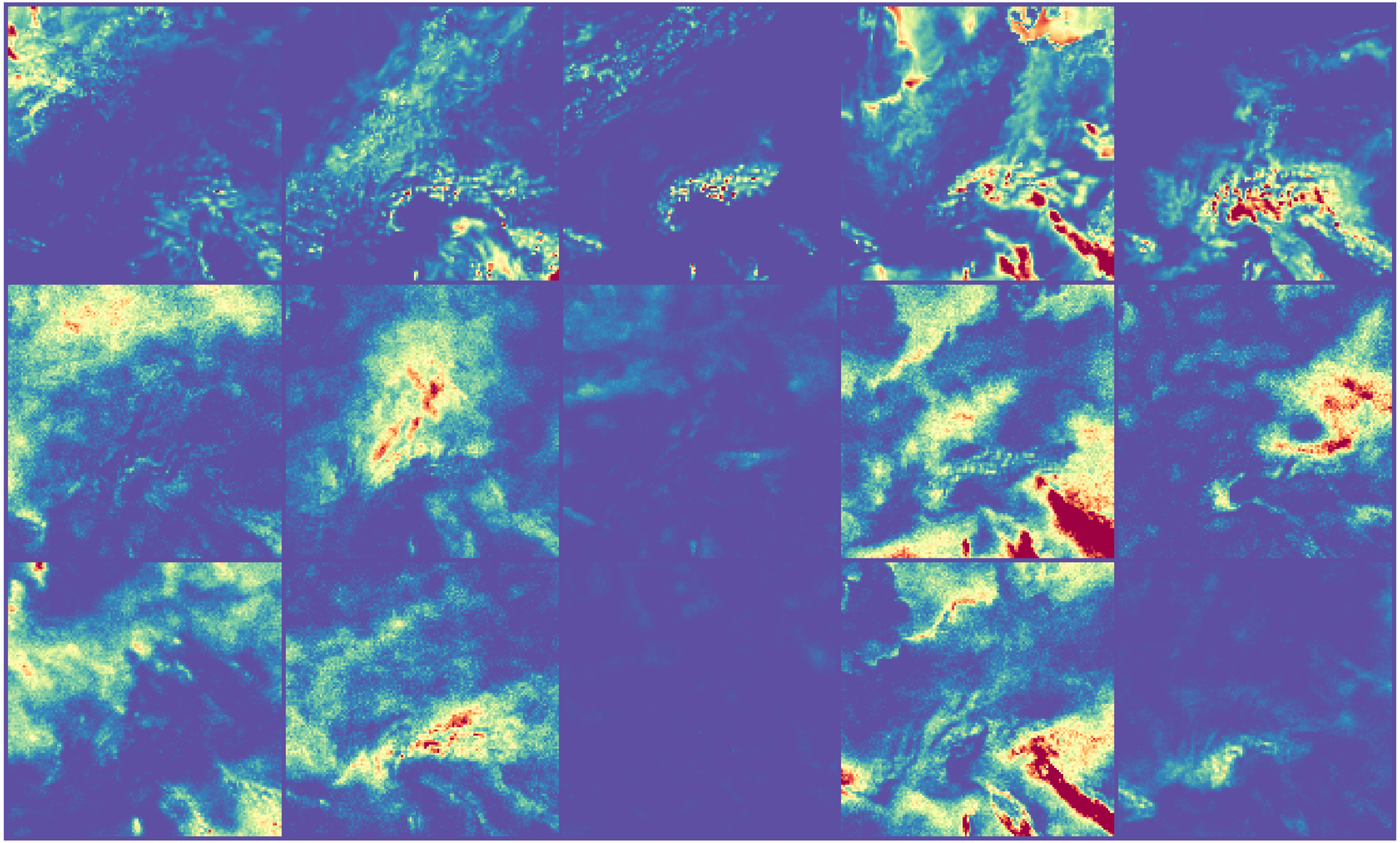


Results: GCM → RCM (pr)

RCM

Sample1

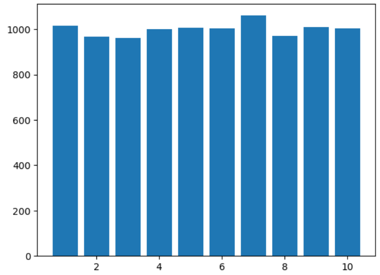
Sample2



Evaluation metrics

Metrics

- **Rank histograms**



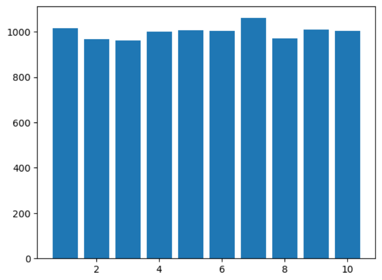
Rank

Flat: Correct variability

Evaluation metrics

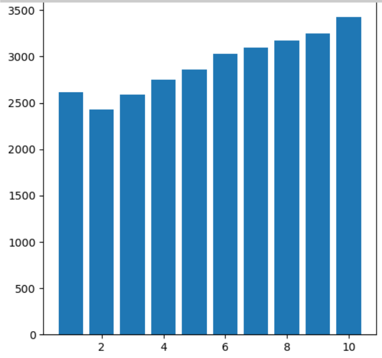
Metrics

- **Rank histograms**

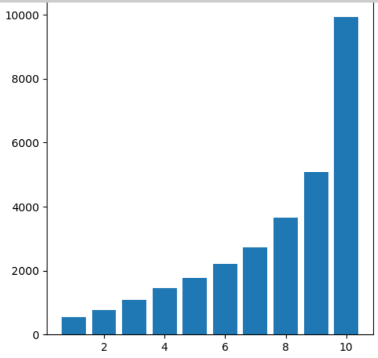


Rank

RH pr, spatial mean



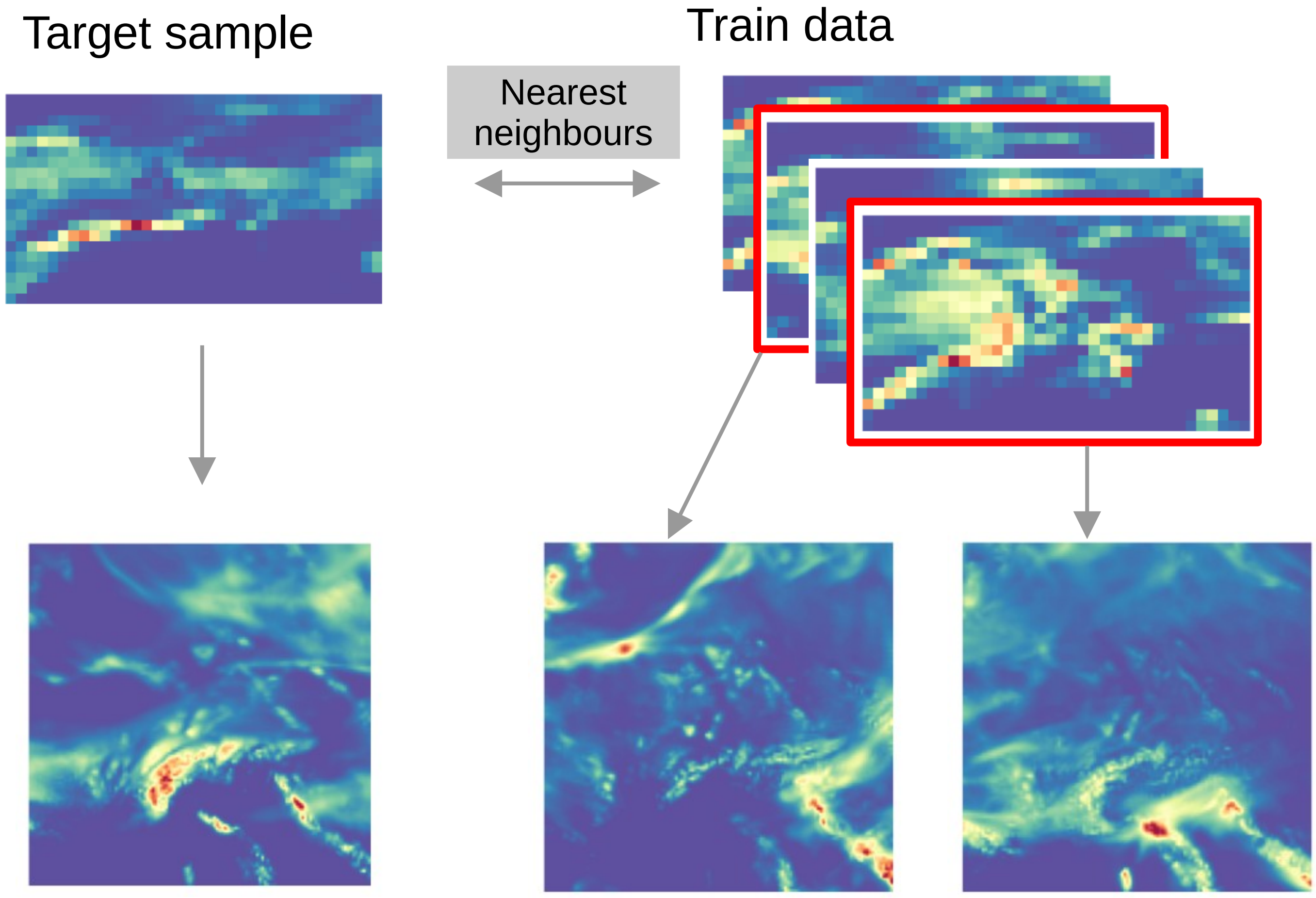
RH pr, spatial max



Flat: Correct variability

Underestimation

Evaluation metrics and benchmarks



Benchmarks

- **Analogues**

Evaluation metrics and benchmarks (pr)

Method	Energy score	Pointwise CRPS	CRPS after max-pooling
Analogues	535	2.36	5.9
Our model	433	1.90	4.8

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Linear model + Easy UQ	437	1.92	14.2
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Method	Energy score	Pointwise CRPS	CRPS after max-pooling
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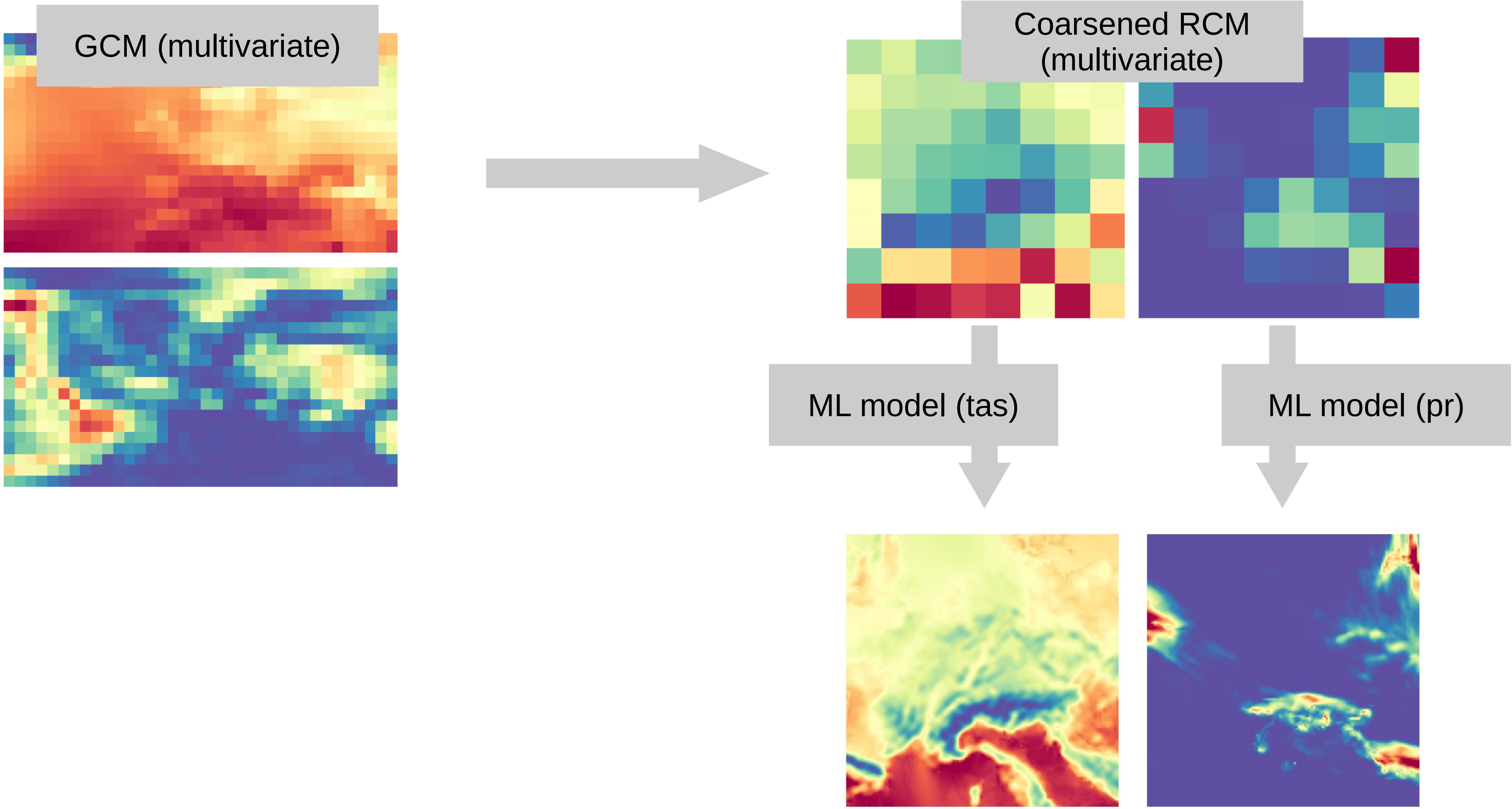
☺

We outperform the benchmarks (almost) everywhere else

☹

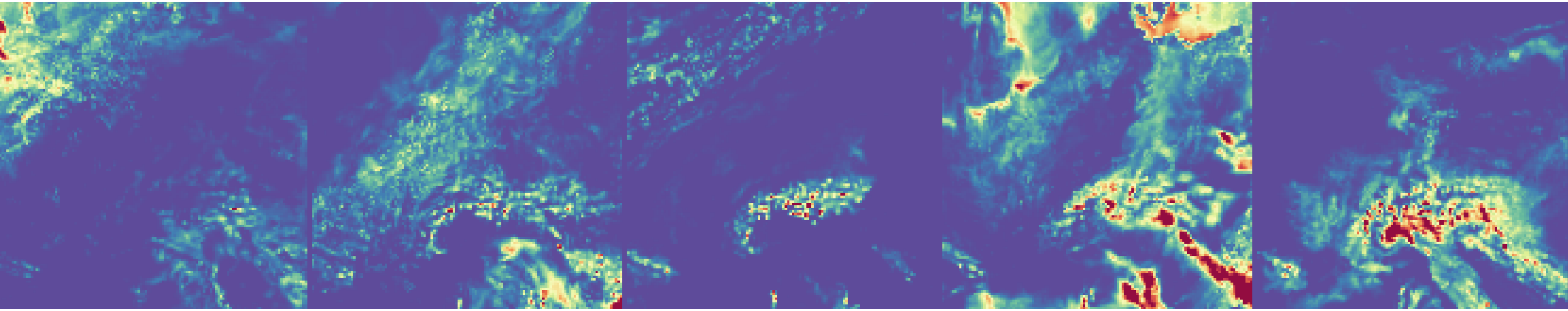
High quantiles for precipiation slightly underestimated

Work in progress: multivariate extension



Take Home Messages

1. Generative models with scoring rules are an easy-to-use and flexible tool.
2. Open questions, e.g. heavy precipitation, multivariate extension, 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

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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.; Kriegsmann, 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 Ml (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.

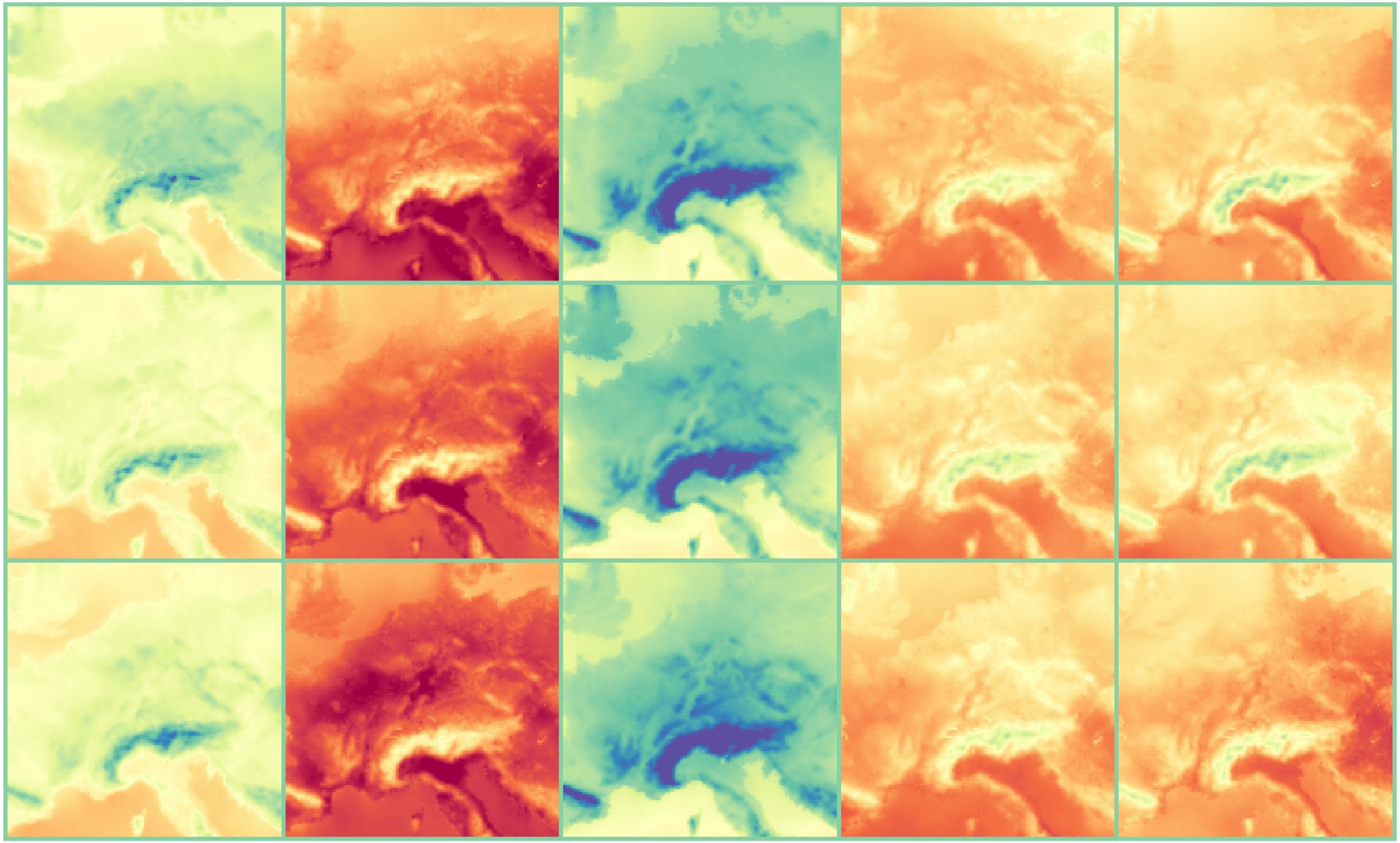
Lorenzo Pacchiardi et al. “Probabilistic Forecasting with Generative Networks via Scoring Rule Minimization”. In: (Dec. 2021). URL: http://arxiv.org/abs/2112.08217.

Results: GCM → RCM (tas)

RCM

Sample1

Sample2

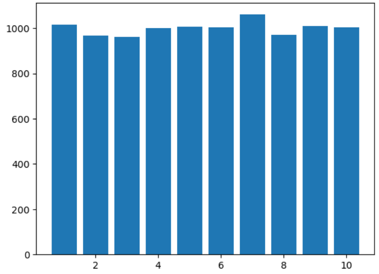


Evaluation metrics

Metrics

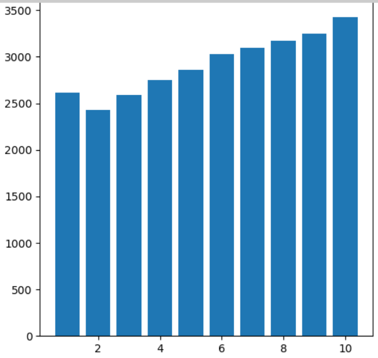
- **Rank histograms**

Flat:
Correct variability



Rank

RH pr, spatial mean



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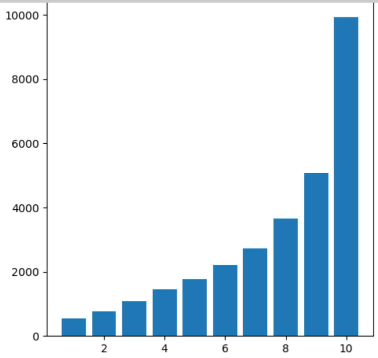
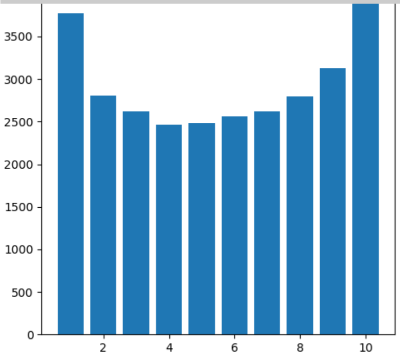


RH tas, spatial mean



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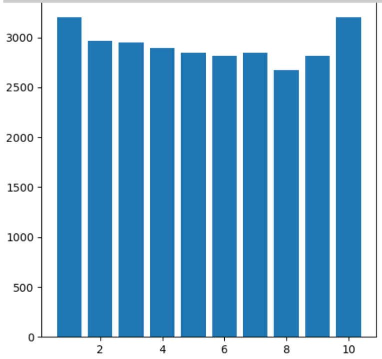
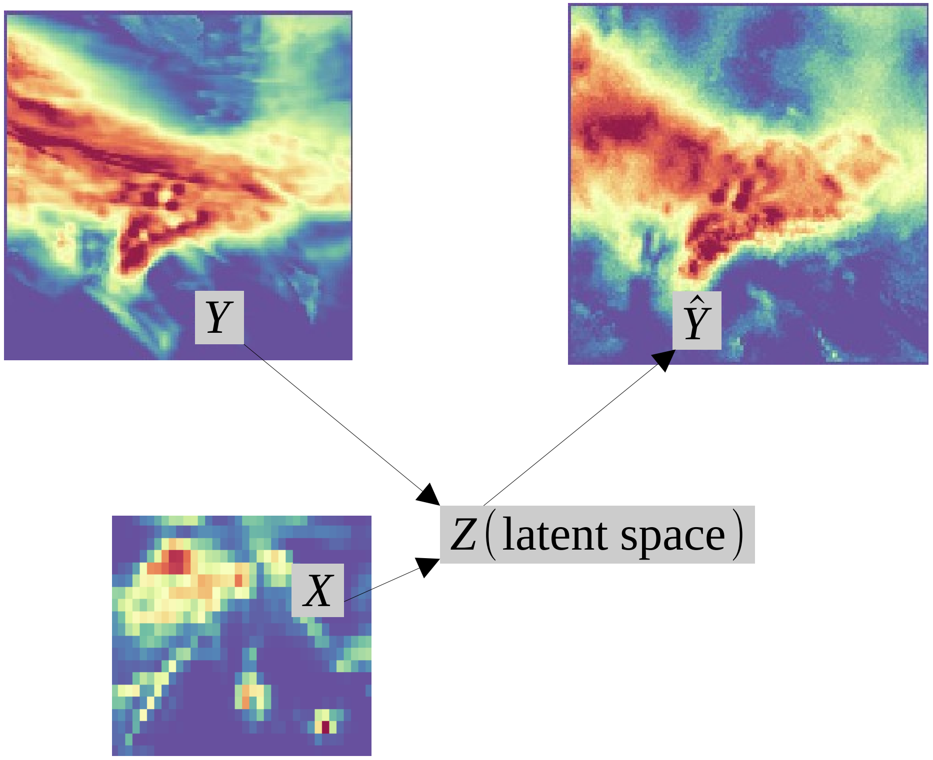


Work in progress: bias correction

Bias-correction to observational data

Dimension reduction



Evaluation metrics and benchmarks

Metrics

- Rank histograms
- Energy score
- Quantiles
- Spatial structure
- Location of maximal value
- ...

Benchmarks

- Linear Model
- Linear Model + EasyUQ
- Analogues