Stochastic downscaling of meteorological fields with deep neural networks

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1) Motivation

- Spatial resolution of atmospheric models is limited
  - Limited Computational resources
  - Parameterization challenges at gray-zone resolution (e.g. convection)
- Alternative: Statistical downscaling
- Recent success with Generative Adversarial Networks (GANs), see e.g. *Harris et al., 2022*
- Here: Downscaling of 2m temperature (T2m)
- Relevance: High spatial variability
  - Locally enhanced heat stress (Fig. 1)
  - Local night frost with trapped cold pools

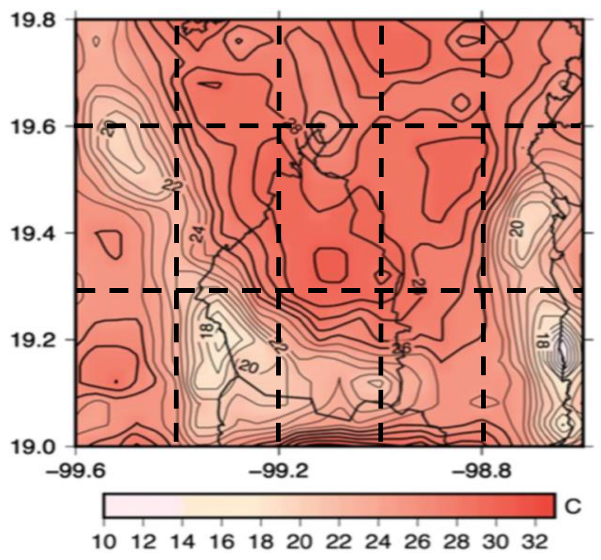

Fig. 1: 90th percentile of Tmax for Mexico City as an example of local heat stress over complex terrain (adapted from *Vargas and Magana, 2020*). The spatial resolution of the ERA5-data (dashed lines) is too coarse to capture the high spatial variability in Tmax.

2) The MAELSTROM project

- MAchinE Learning for Scalable meTeORology and cliMate
- Coordination by ECMWF
- Project duration: April 2021 – April 2024
- Objective: efficient use of new machine learning capacities on supercomputers for the Weather and Climate community
- Collaboration between meteorologists, software developers and HPC specialists

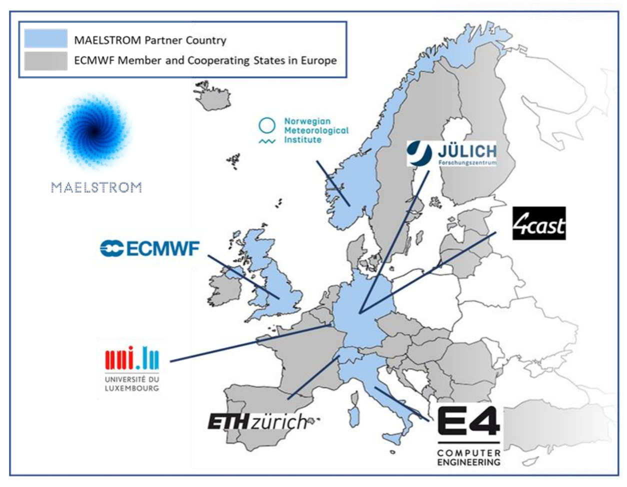

Fig. 2: Map which shows the headquarters of all partners of the MAELSTROM consortium.

ML applications under development

(1) Blend citizen observations and numerical weather forecasts

(2) Incorporate social media data into prediction framework

(3) Develop neural network emulators for faster weather forecast models & data assimilation

(4) Improve ensemble predictions in forecast post-processing

(5) Improve local weather prediction in forecast post-processing → Statistical downscaling

(6) Support energy production with bespoke weather forecasts

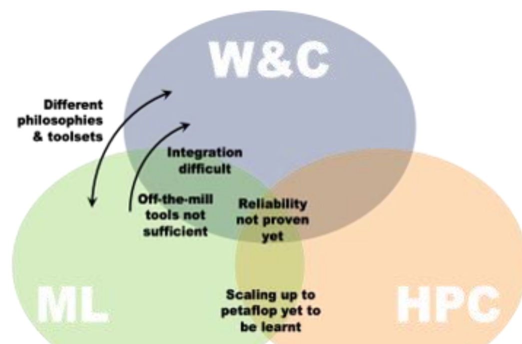

Fig. 3: Interacting domains in the MAELSTROM project.

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3) Downscaling with a U-Net

- First application: Pure downscaling of 2m temperature from IFS forecasts
- Data: model data with $\Delta x_{coa} = 0.8°$ coarsened from IFS forecasts with $\Delta x_{IFS} = 0.1°$
- Task: Learn mapping from Δx_{coa} to Δx_{IFS}
- Model: U-shaped convolutional encoder-decoder network (U-Net), see Fig. 4
- Only additional (static) predictor: surface elevation z_{sfc}
- Dataset:
  - Training data: 2016-2019; validation and test data: 2020
  - Target domain: 128x96 grid points ($\Delta x = 0.1°$) over Central Europe
  - Data times:
    1. Initial time of 12 UTC-runs
    2. Data from 10-16 UTC + augmentation

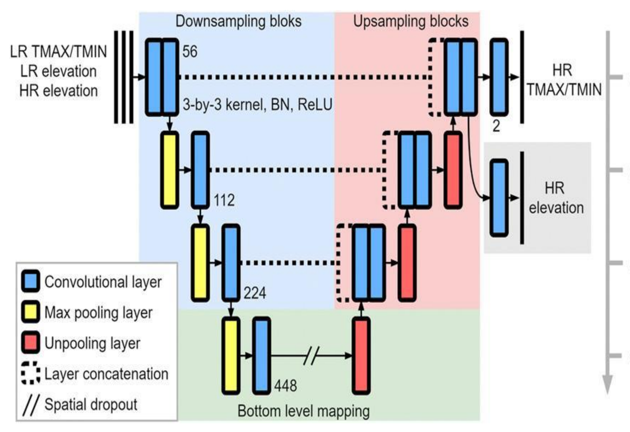

Fig. 4: Illustration of the U-Net used for downscaling the 2m temperature. From *Sha et al., 2020*.

You want to run the downscaling U-Net on your own?

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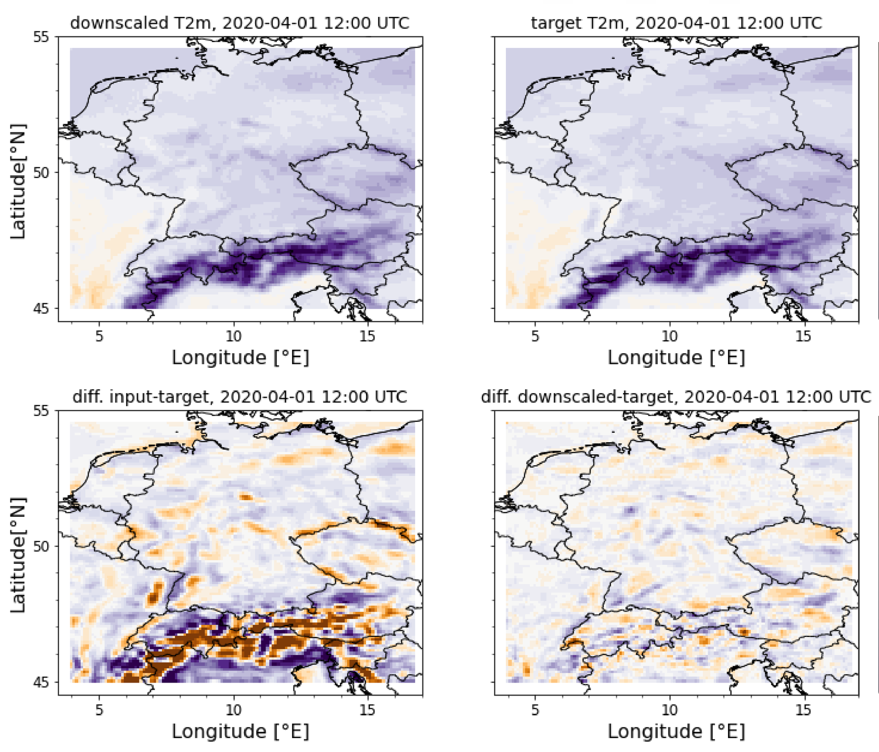


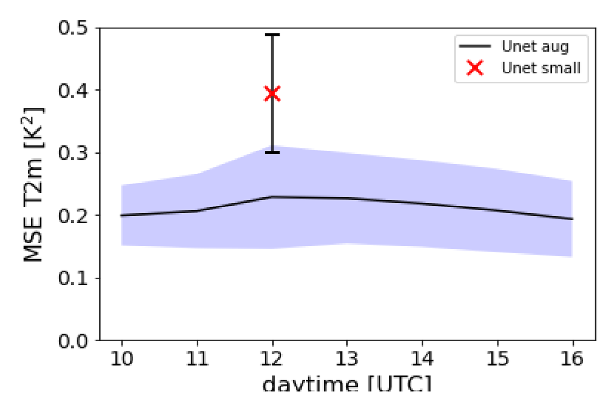


Fig. 5: Evaluation of the U-Net trained on the augmented dataset.
Left: Example for downscaled T2m-field from the test dataset.
Bottom right: MSE for the U-Nets trained on the small and augmented dataset.

4) Downscaling with a Wasserstein GAN

- **Target**
  - 'Real' downscaling: Map short-range forecasts (lead times 6-17 hours) from ERA5 ($\Delta x_{coa} = 0.8°$) to IFS ($\Delta x_{IFS} = 0.1°$)
  - Generalize application to arbitrary daytimes and season
- **Approach**
  - Encode planetary boundary layer (PBL) state: T(850 hPa, 925 hPa), $\mathbf{v}_h$(10m), PBL height, surface heat fluxes (+ z_{sfc} and T(2m))
  - Integrate U-Net into Wasserstein GAN (Fig. 6)

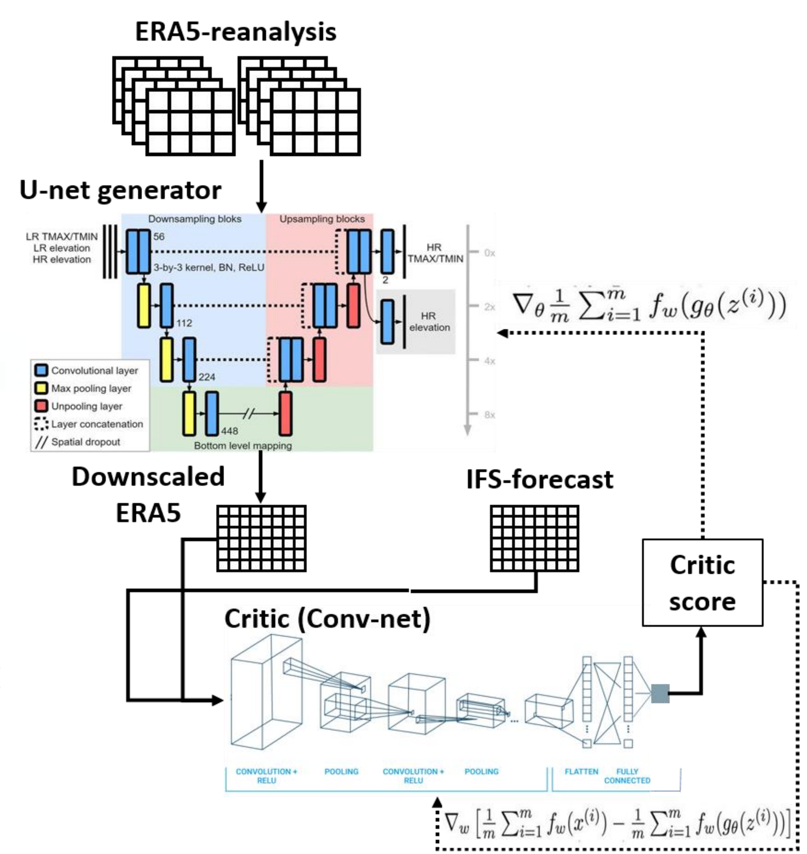
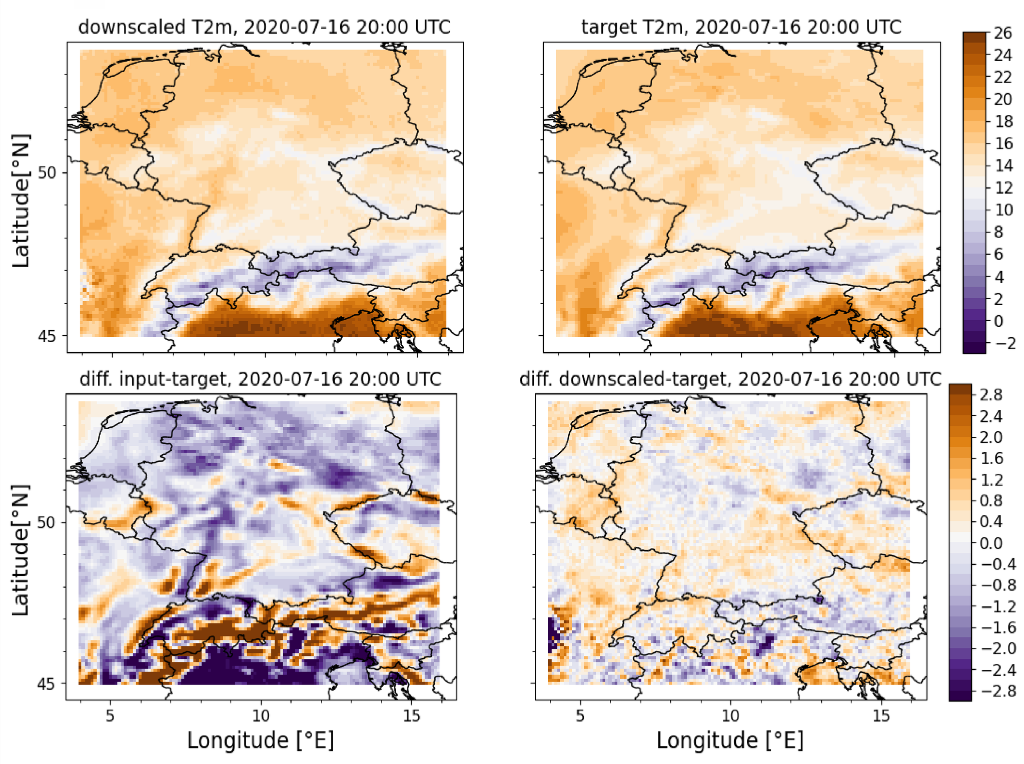


Fig. 6: Illustration of the ERA5-DeepHRES architecture.



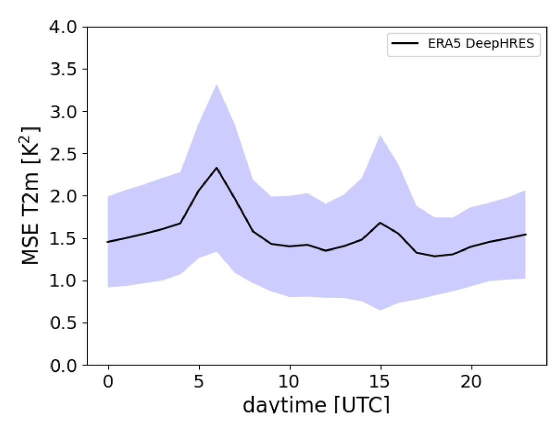


Fig. 7: Evaluation of the Wasserstein GAN.
Left: Example for downscaled T2m-field from the test dataset.
Bottom right: Hourly MSE averaged over the test dataset period for the trained Wasserstein GAN.

5) Conclusion and outlook

- Improve downscaling model
  - Fine-tune hyperparameters and include time embeddings
  - Improve model architecture
  - Comprehensive evaluation
- Downscaling on kilometre-scale
  - ICON → COSMO-D2
  - Include observations
  - Swin Transformer architecture (see *Liu et al., 2021*)

References:

[1] Vargas and Magana, WACS, 12.3, 351-365, 2020.
[2] Sha et al., JAMC, 59.12, 2057-2073, 2020.
[3] Harris et al. *arXiv preprint arXiv:2204.02028*, 2022.
[4] Liu et al., Proc. IEEE Int. Conf. Comput. Vis., 2021.

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