Benchmarking Deep Learning Models for Wind Speed Downscaling

Luca Schmidt[1,2] Nicole Ludwig[1]

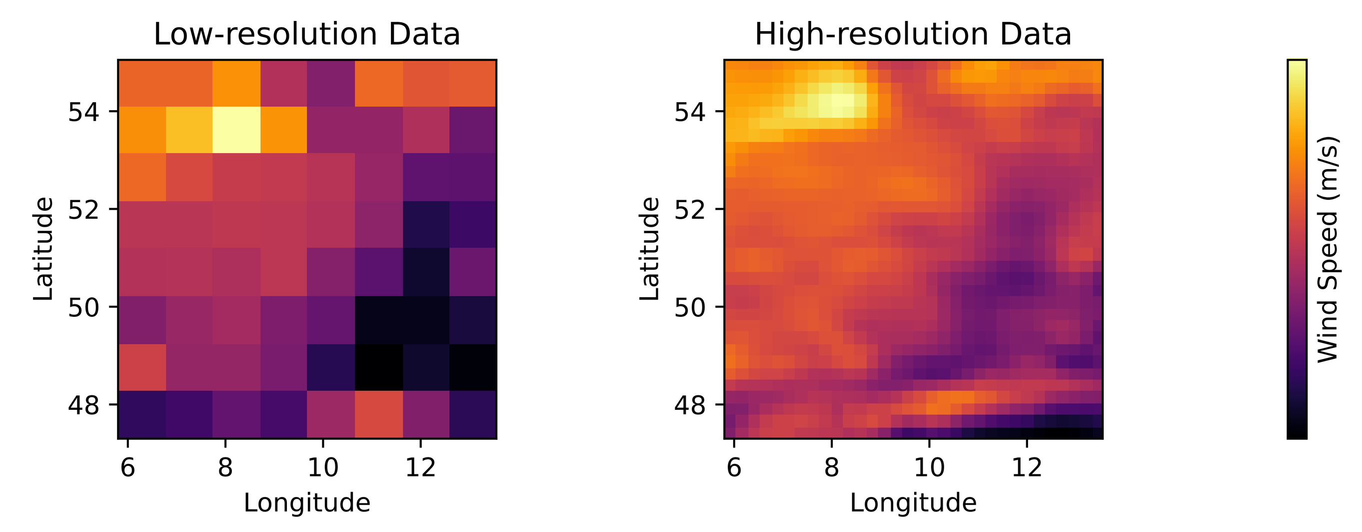
[1]Cluster of Excellence Machine Learning, University of Tübingen, Germany [2]Tübingen AI Center, Germany

Motivation

- > Efficient wind turbine placement requires information about local wind speeds.
- > However, the spatial resolution of climate projections is typically too coarse.
- > We present a **comprehensive benchmark** of state-of-the-art deep learning-based models for statistical downscaling of weather data.

Data

Wind velocity (100m) ERA5 reanalysis data at $0.25°$ spatial & hourly temporal resolution:



We downscale patches of size 8×8 (LR) to size 32×32 (HR) over Germany.

Super-resolution (SR) Methods

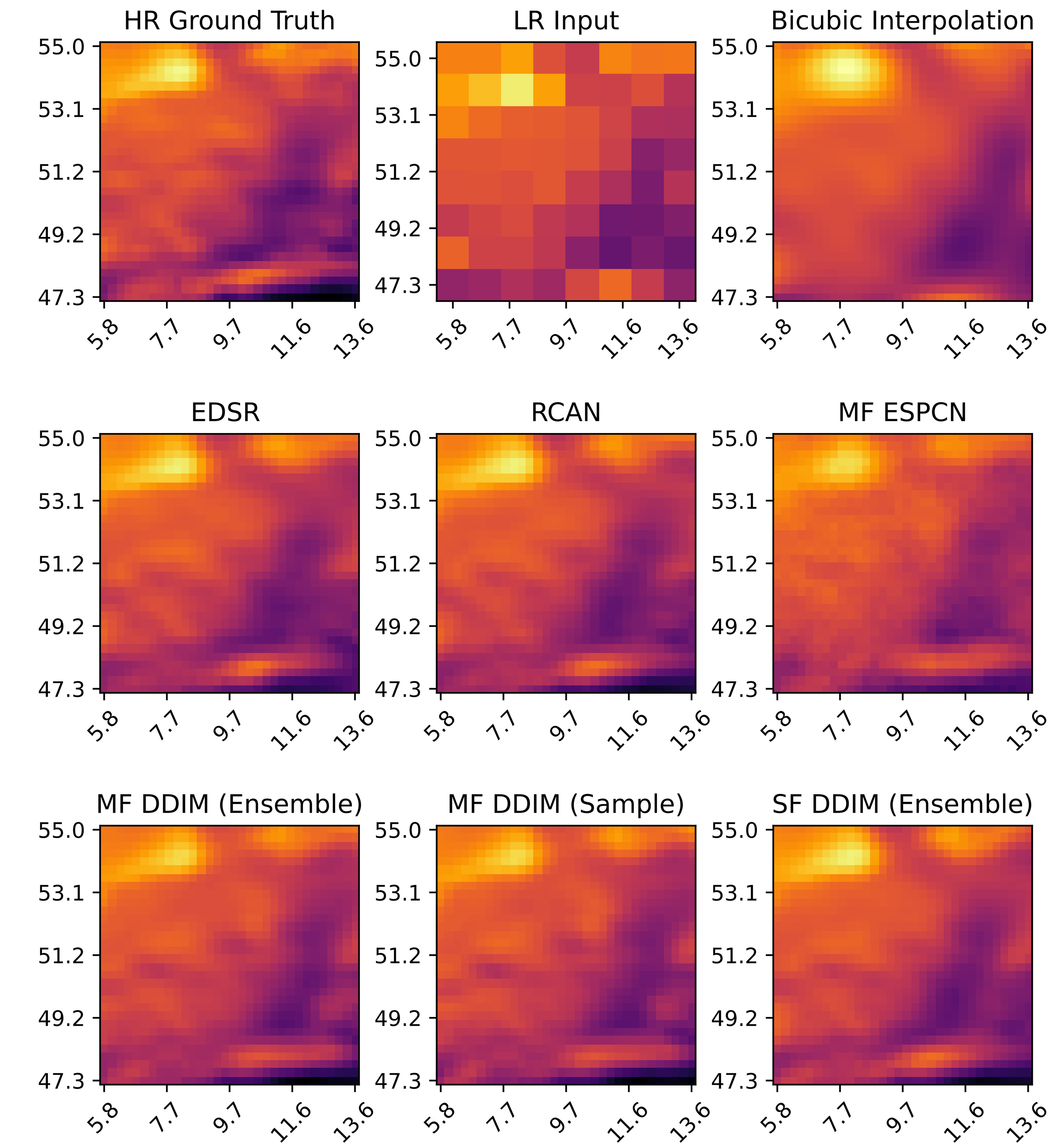
The benchmark ranges from interpolation baselines to various prominent SR models:

	Method	Model Name	Parameters	Inference Time*
Image SR	CNN-based	EDSR [1]	1,516,418	65 s
Image SR	Attention-based	RCAN [2]	15,587,602	674 s
Video SR	Spatio-temporal	multi-frame ESPCN [3]	5,6826	12 s
Image SR	Diffusion Model	single-frame DDIM [4]	113,618,242	23210 s
Video SR	Diffusion Model	multi-frame DDIM**	113,624,002	26206 s
Interpolation	Bicubic			

* Inference time for the computation of one year of downscaled data.

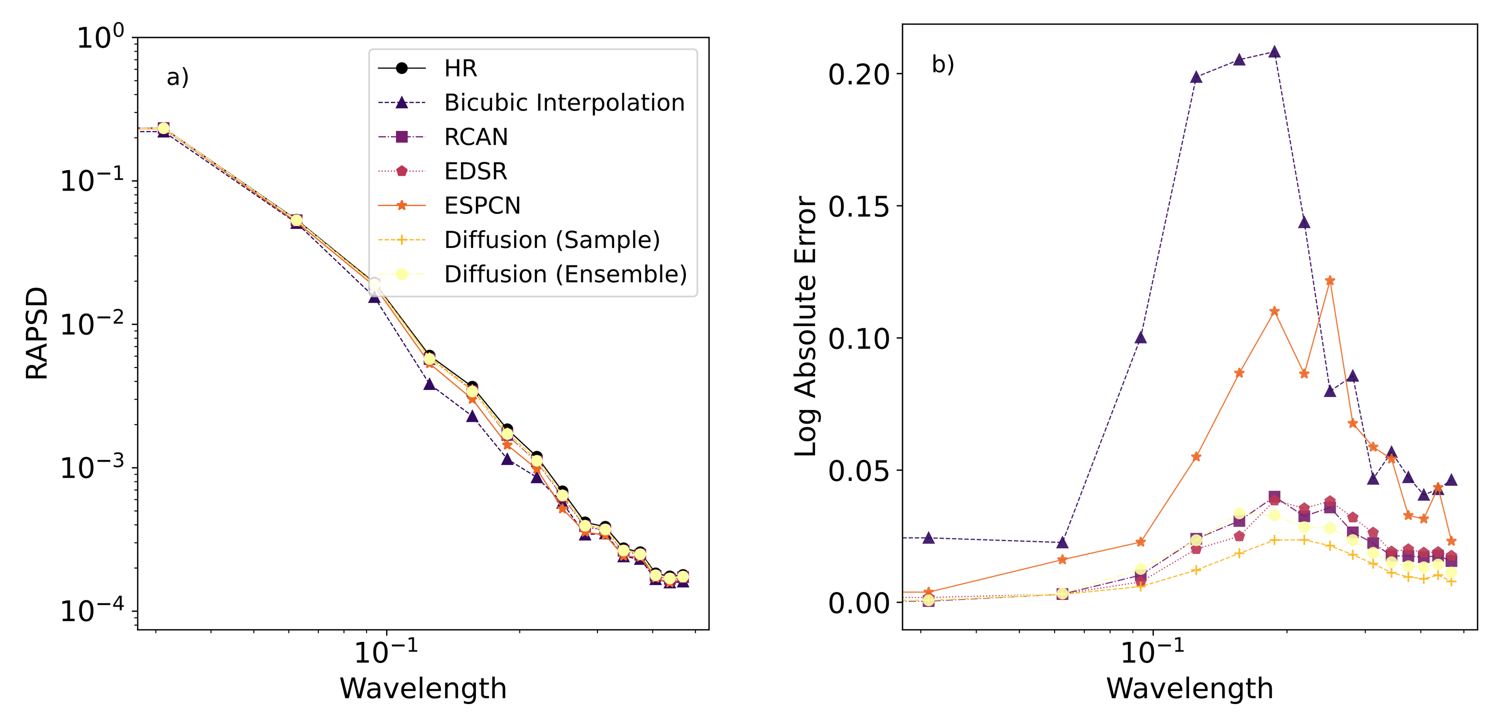
** The multi-frame model versions use three consecutive LR patches to downscale each middle patch.

Results: Downscaled Wind Speed Fields.



Results: Differences in spatial variability.

We evaluate the spatial variability using the Radially Averaged Power Spectral Density (RAPSD):



(a) RAPSDs of the wind speed fields as an average over the test set. (b) The absolute error of the log-transformed spectra w.r.t. the ground truth is shown to highlight the differences.

Preliminary Findings

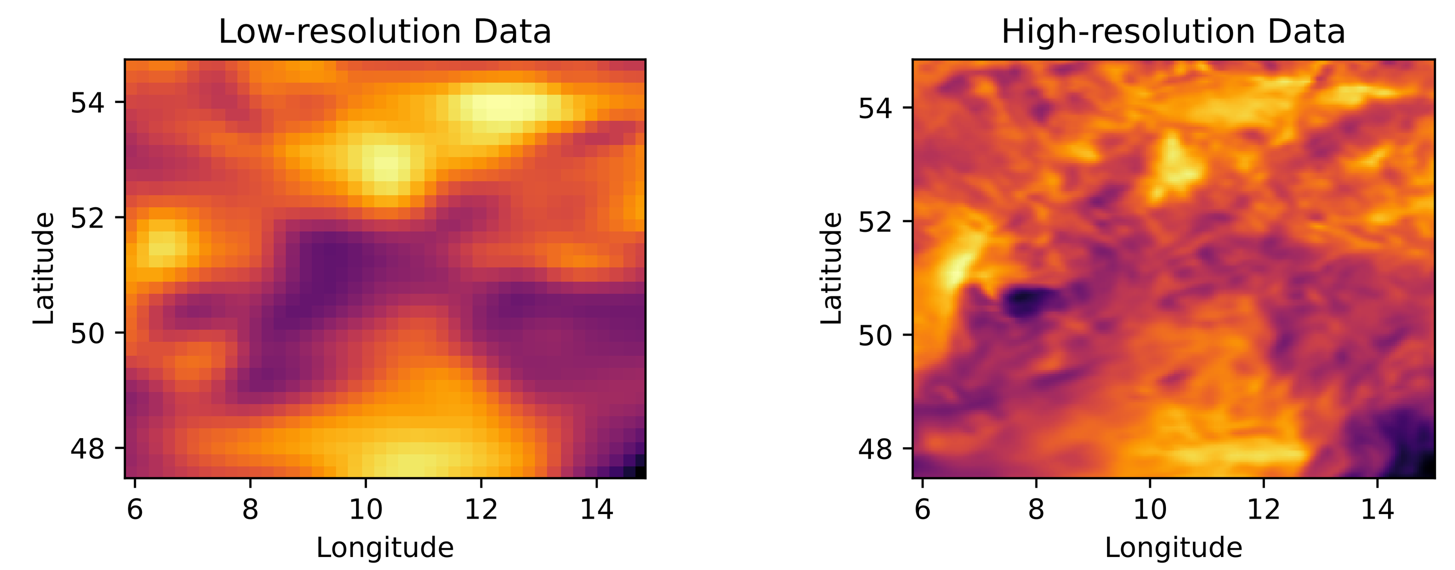
- > Multi-input & multi-output prediction using u & v velocity components improves accuracy compared to single-input & single-output prediction using wind speed.
- > Fairly 'easy' task to downscale wind speed by factor 4:

Model	PSNR	SSIM	MAE
EDSR	43.6974	0.9773	0.0054
RCAN	43.9422	0.9778	0.0053
ESPCN	41.0820	0.9583	0.0084
DDIM $_{\text{sf, e}}$	44.4727	0.9814	0.0048
DDIM $_{\text{sf, s}}$	43.9046	0.9790	0.0053
DDIM $_{\text{mf, e}}$	**45.2625**	**0.9844**	**0.0045**
DDIM $_{\text{mf, s}}$	44.8372	0.9828	0.0047
Interpolation	32.3057	0.8900	0.0178

- > The Diffusion models outperform all other models across all metrics, both when evaluated on a single sample and when averaged over ensemble members.

Future Research

- > Extending models to more 'complex' downscaling task: ERA5 (0.25°) → COSMO REA6 (0.05°)



- > Evaluating probabilistic models by CRPS of several ensemble members.
- > Evaluating on downstream task to quantify the models impact for wind power assessment.

References

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[3] Jose Caballero, Christian Ledig, Andrew Aitken, Alejandro Acosta, Johannes Totz, Zehan Wang, and Wenzhe Shi. Real-time video super-resolution with spatio-temporal networks and motion compensation. In Proceedings of the IEEE conference on computer vision and pattern recogni- tion, pp. 4778–4787, 2017.

[4] Jiaming Song, Chenlin Meng, and Stefano Ermon. Denoising diffusion implicit models. arXiv preprint arXiv:2010.02502, 2020.

Contact & Acknowledgments

EBERHARD KARLS UNIVERSITÄT TÜBINGEN

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imprs-is

 luca.schmidt@uni-tuebingen.de