

# Building Machine Learning Limited Area Models

Kilometer-Scale Weather Forecasting in  
Realistic Settings

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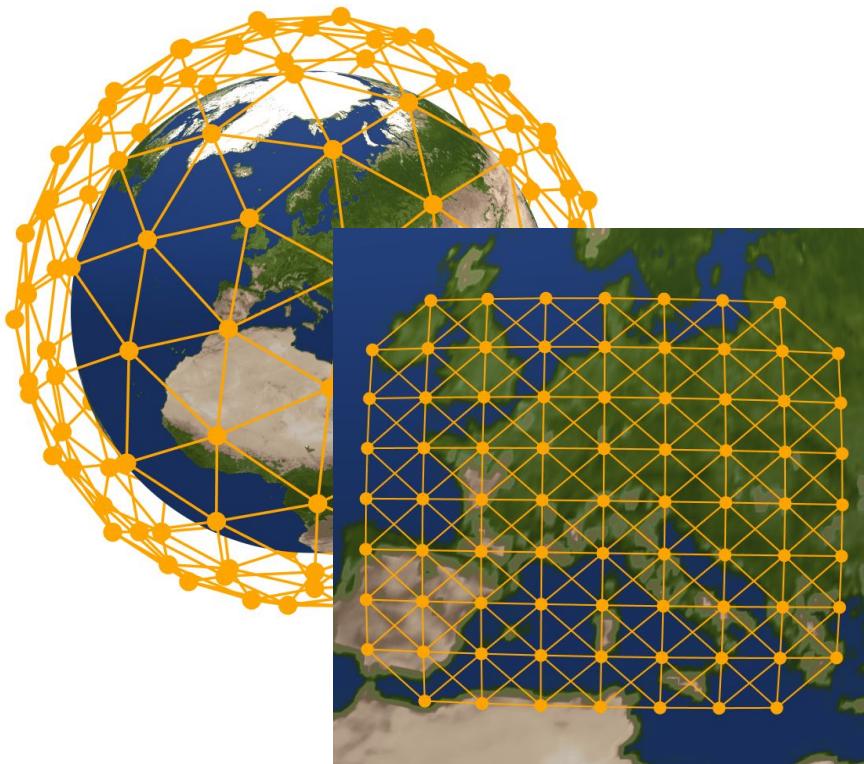
MeteoSwiss, ETH Zurich



**MeteoSwiss**

**ETH** zürich

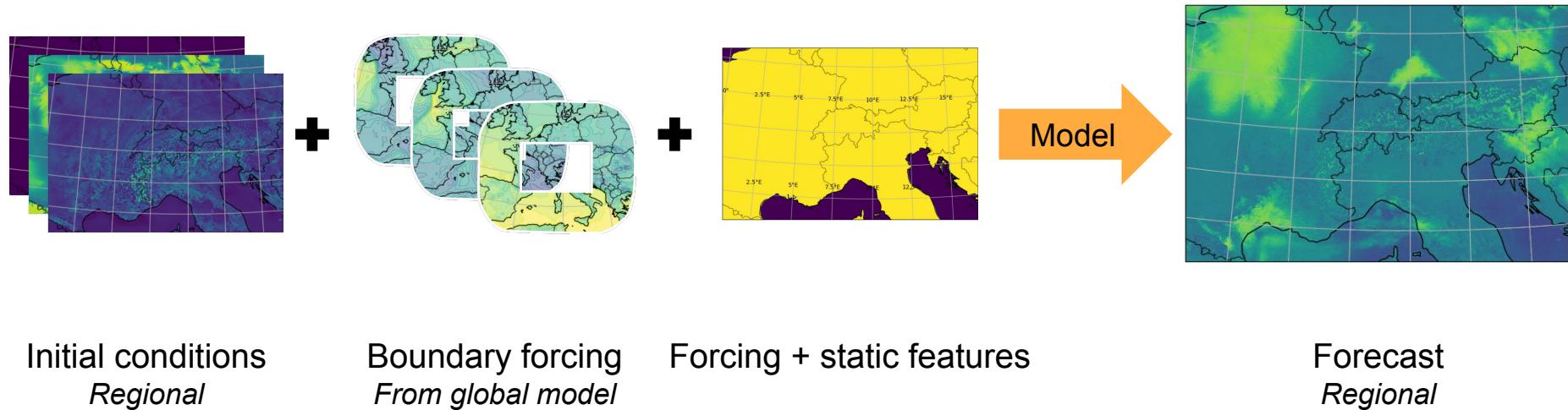
# Machine Learning Weather Prediction



## Regional Models:

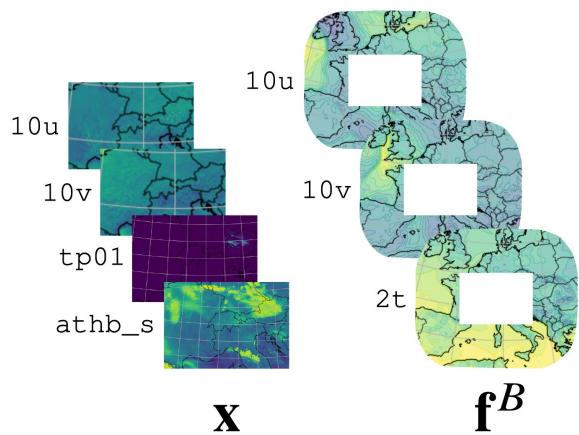
- Higher resolution
- Model challenging processes
- Utilize regional data

# The Limited Area Forecasting Problem

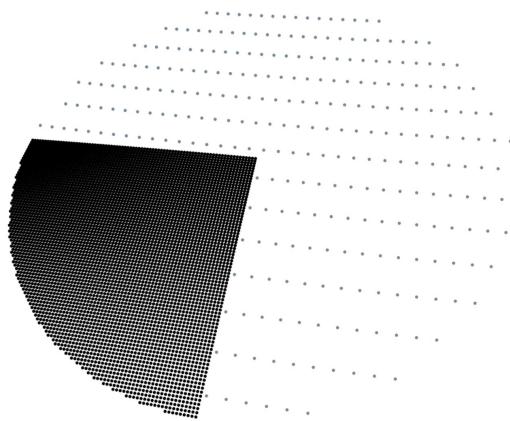


**This project:** Realistic setting, forced by global forecast (IFS)

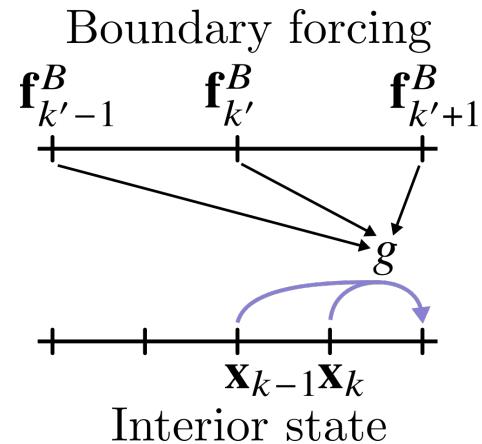
# A Framework for Machine Learning LAMs



Different atmospheric variables

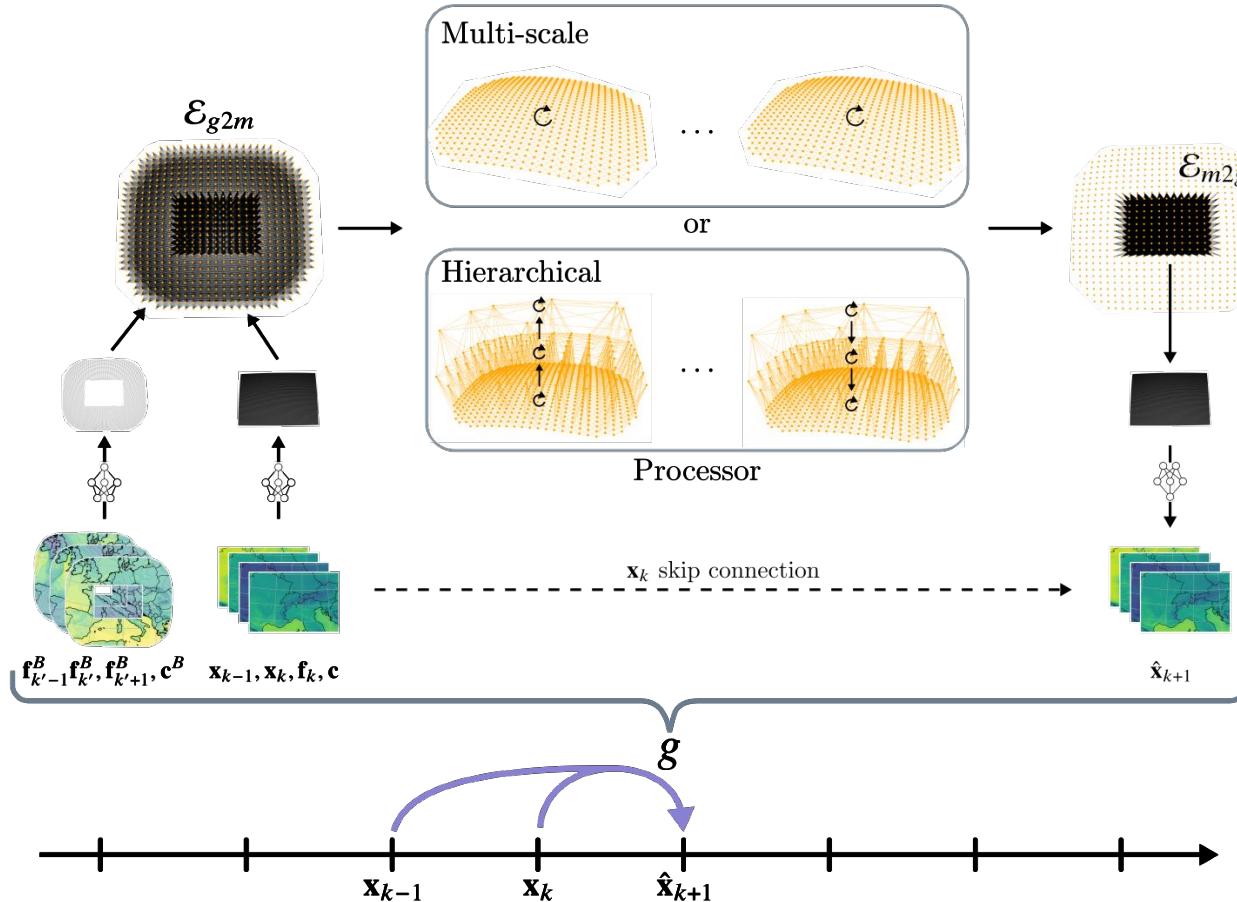


Different grid layouts

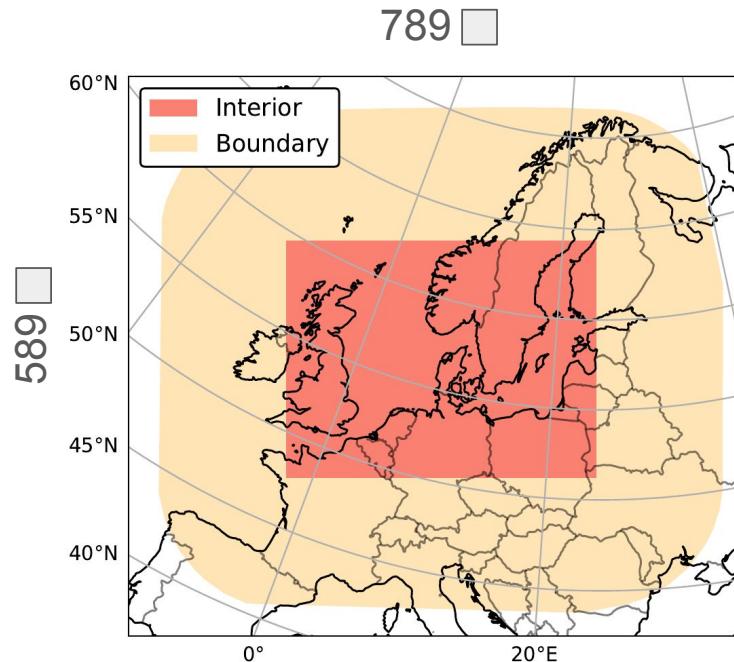


Different length of time steps

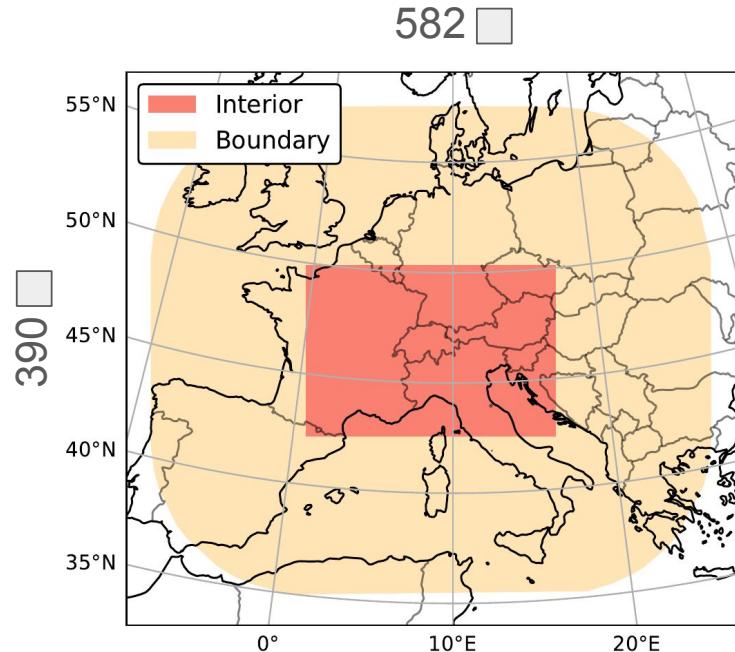
# Graph-based Model



# Datasets



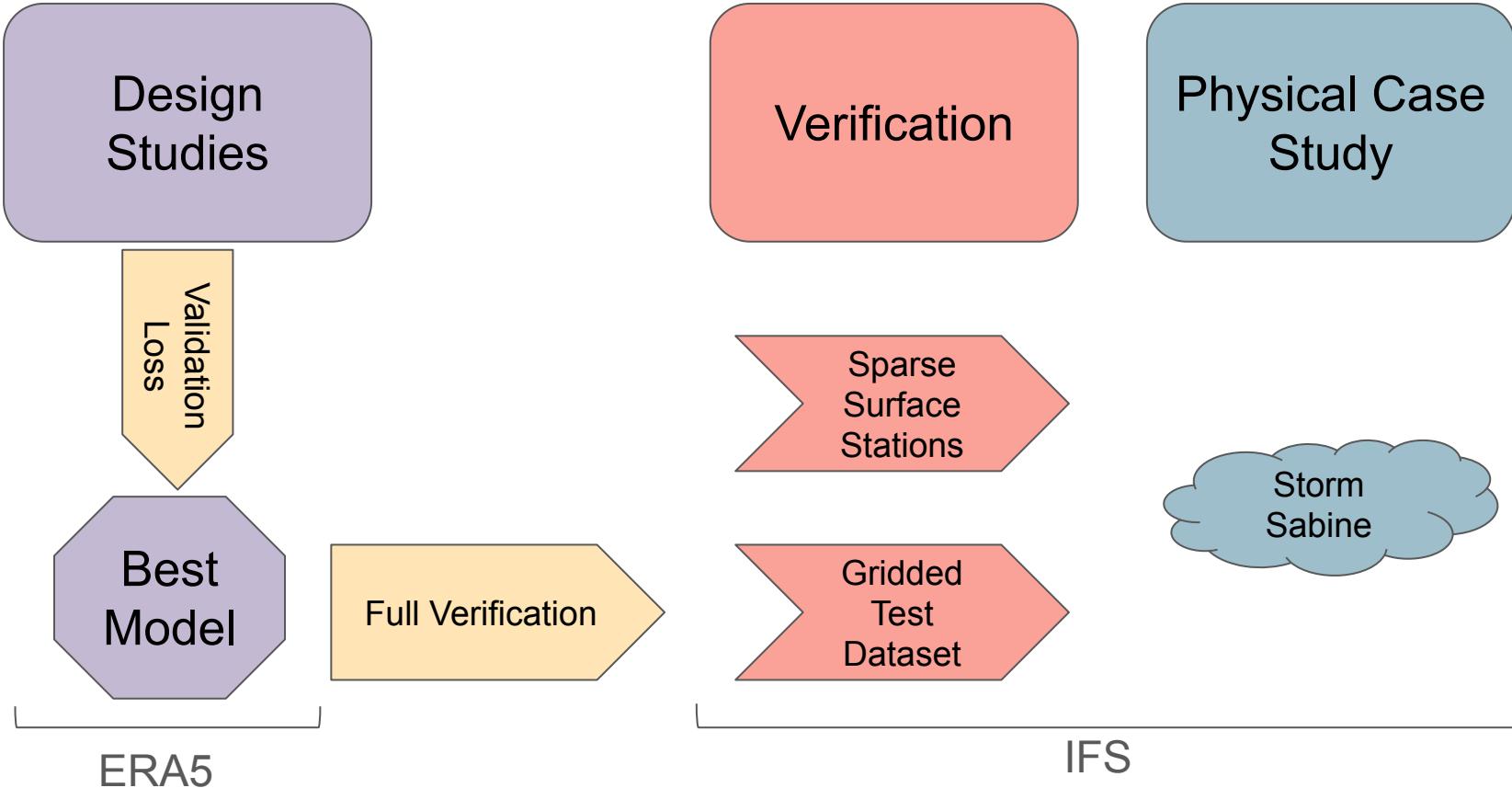
DANRA - 2.5km - 3h - 21 years



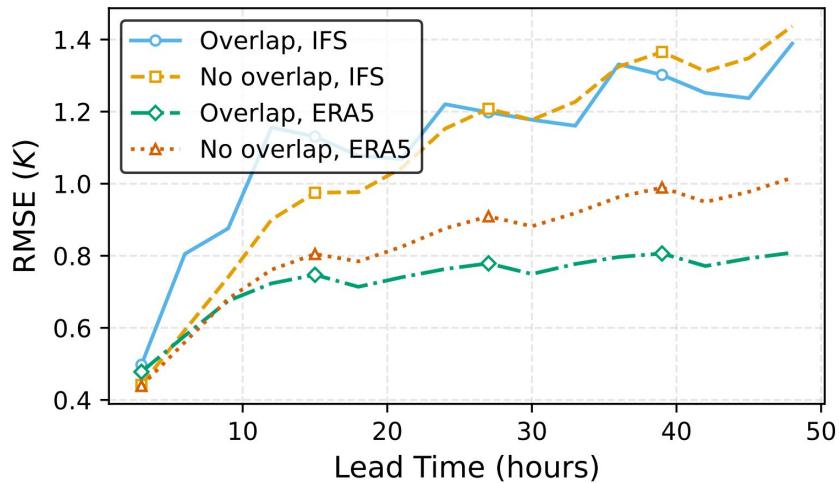
COSMO - 2.2km - 1h - 4 years

Boundary forcing: ERA5/IFS -  $0.25^\circ$  - 6h

# Experiments

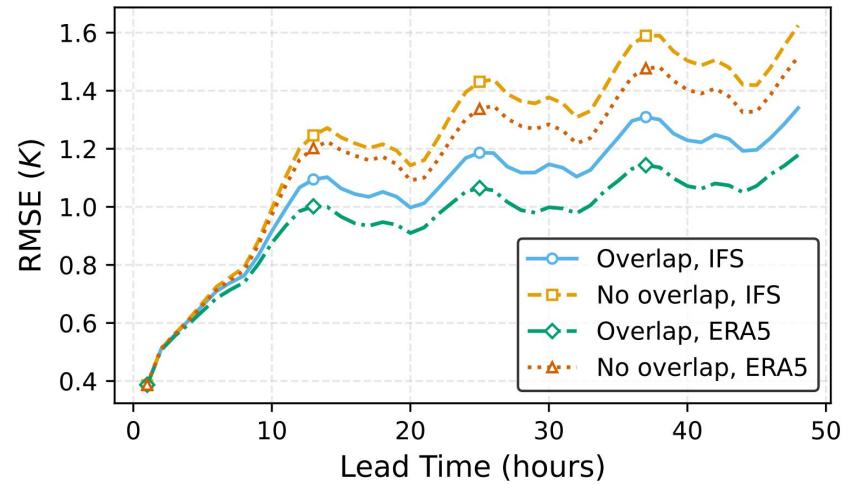


# Design Studies - Boundary Type



(a) 2 m temperature ( $2\tau$ )

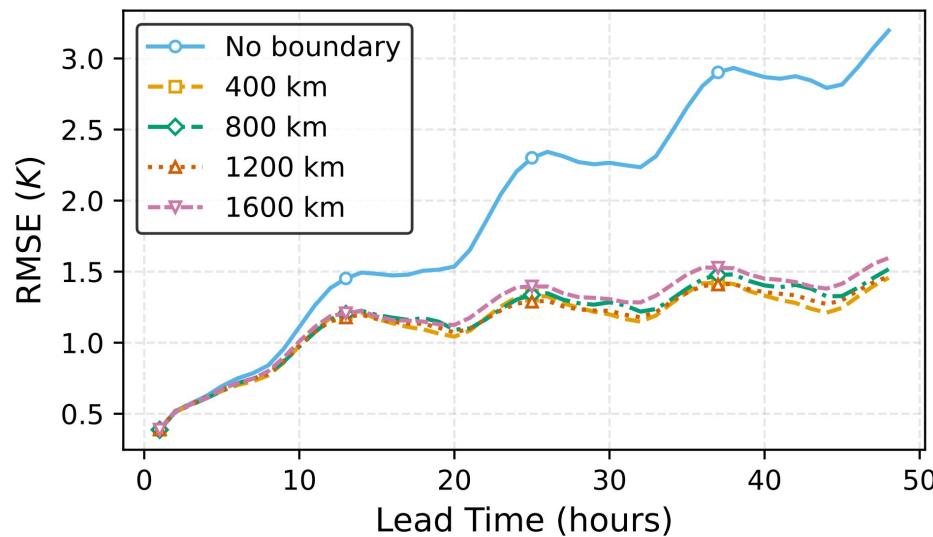
DANRA  
Overlap less important  
Growing error inherited from IFS



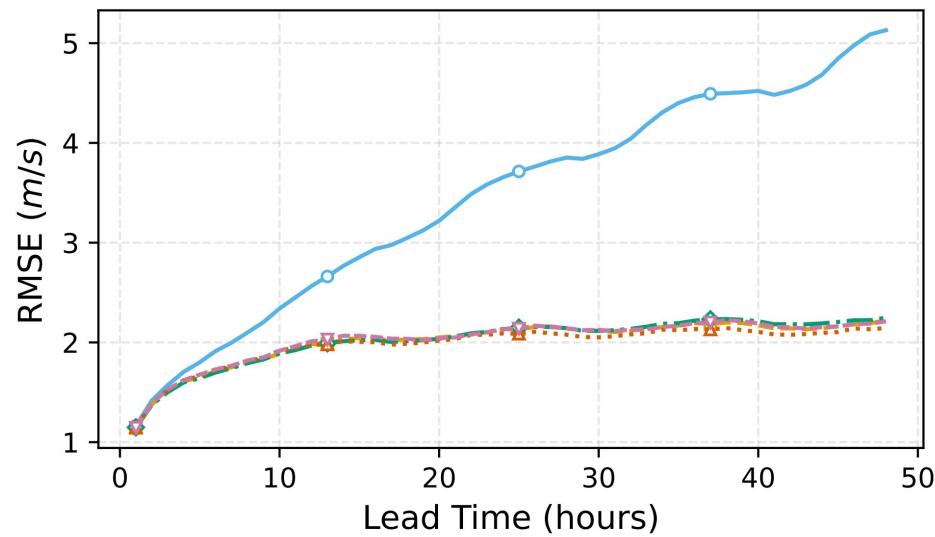
(a) 2 m temperature ( $2\tau$ )

COSMO  
Overlap more important  
Forecasting vs. downscaling

# Design Studies - Boundary Width - COSMO



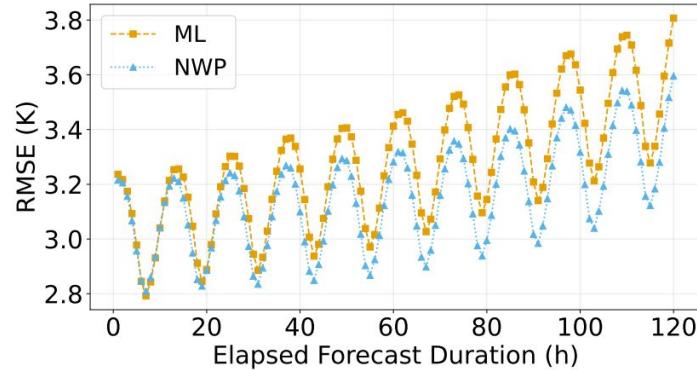
(a) 2 m temperature ( $2t$ )



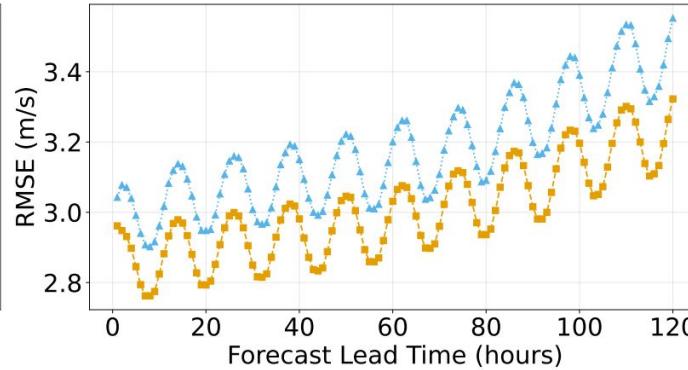
(b) 10 m wind

The boundary is important but can be smaller than we expected

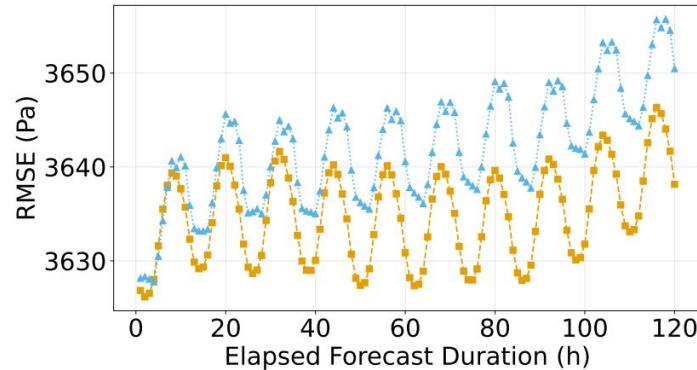
# Verification Sparse - COSMO



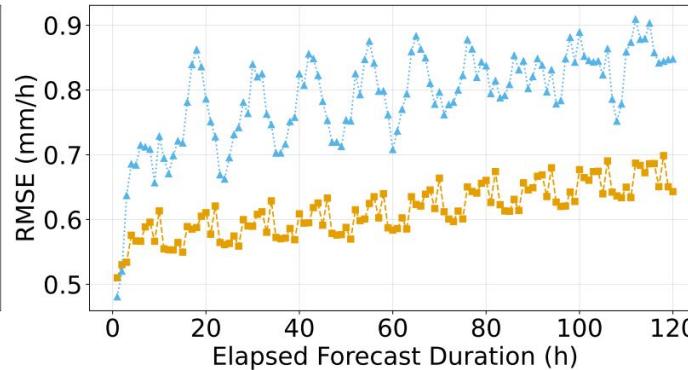
(a) 2 m temperature ( $2t$ )



(b) 10 m wind

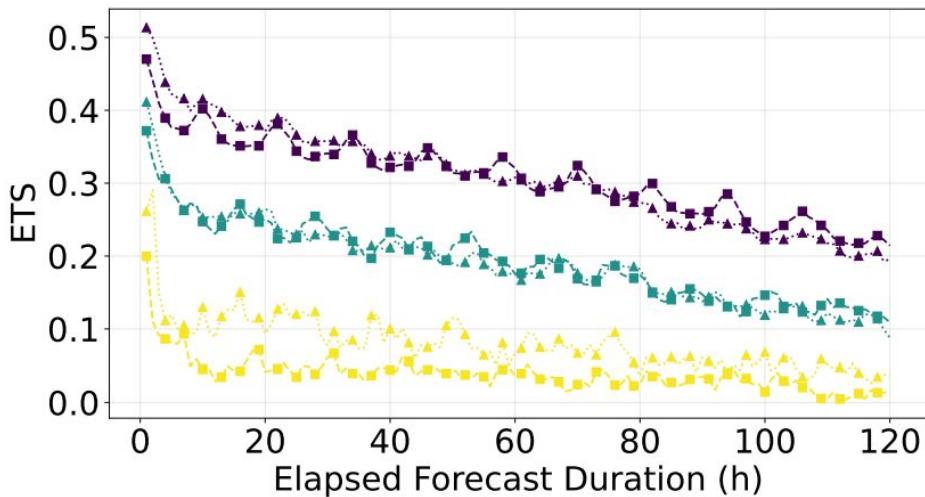


(c) Surface pressure (sp)

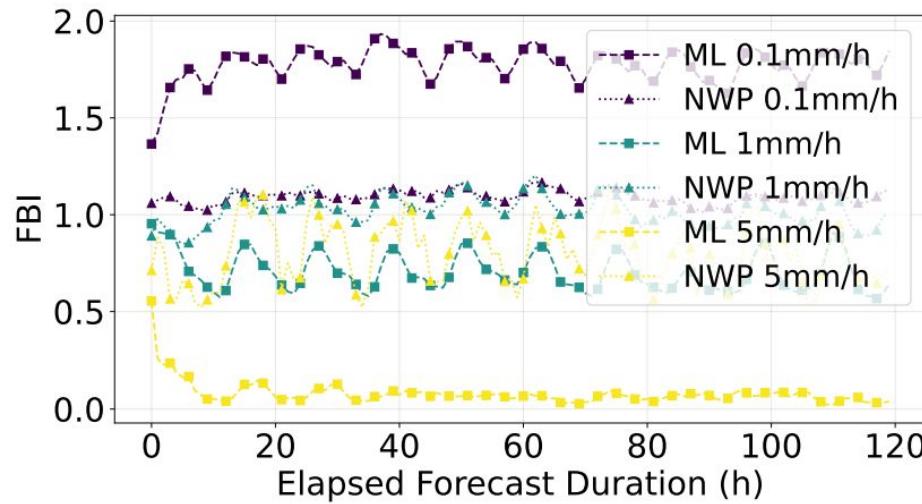


(d) Precipitation (tp01)

# Verification Sparse - Threshold Based - COSMO



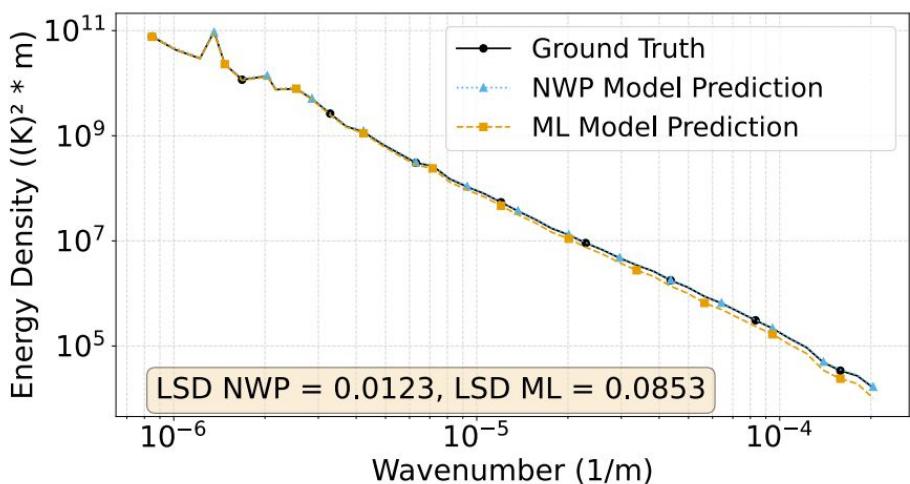
(d) Precipitation ( $\tau_{p01}$ ) ETS



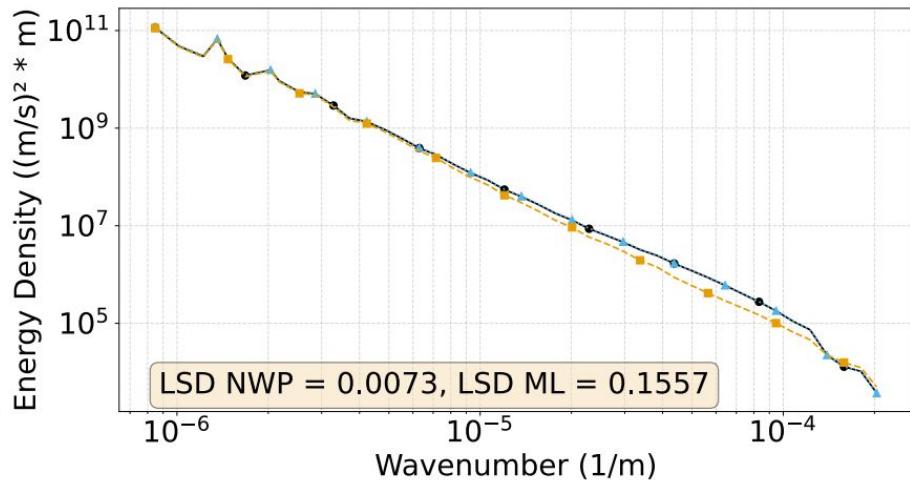
(c) Precipitation ( $\tau_{p01}$ ) FBI

Verifying the model with appropriate figures and metrics is crucial

# Verification Gridded - Energy Spectra - DANRA



(a) 2 m temperature ( $2t$ )

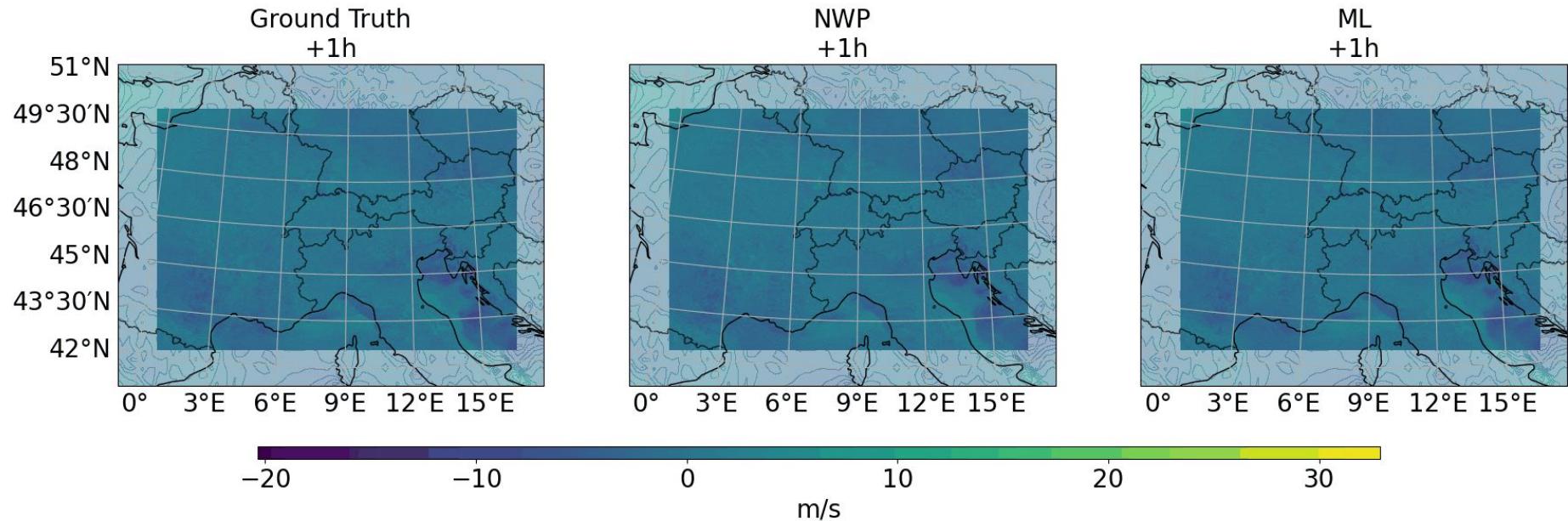


(b) 10 m wind-component ( $10u$ )

Energy spectra showing only slight over-smoothing of high frequencies

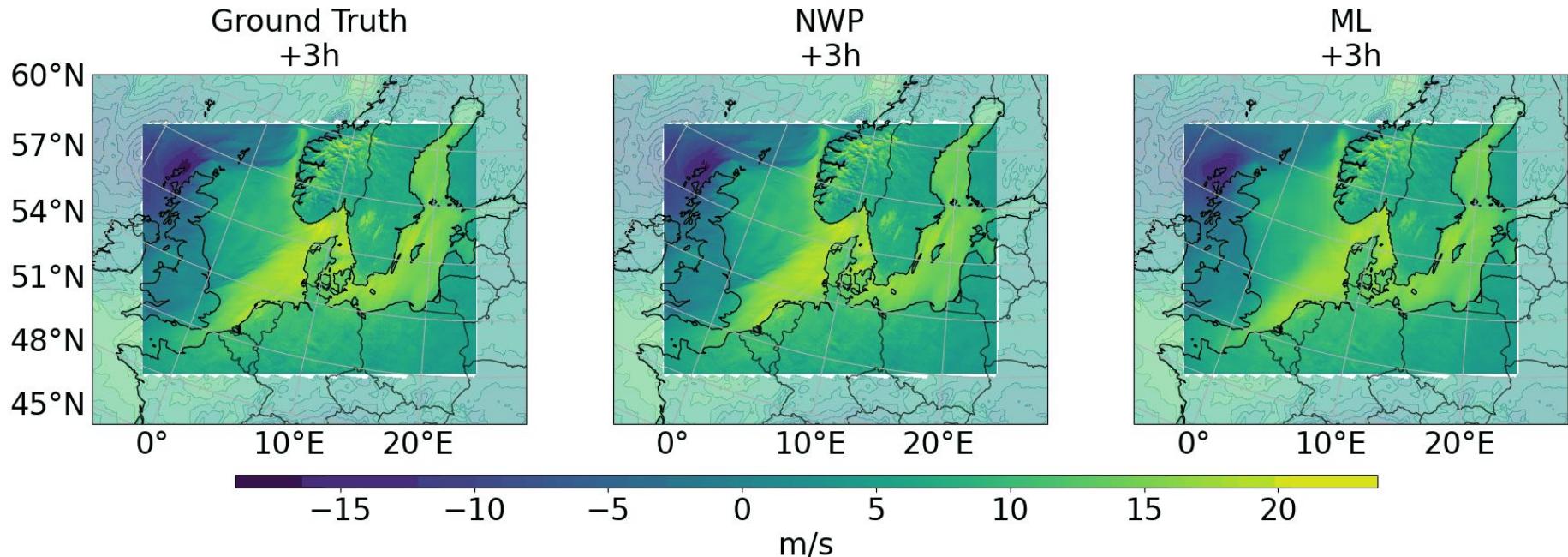
# Case Study Sabine - COSMO

wind\_u\_10m starting at 2020-02-08 - 00 UTC



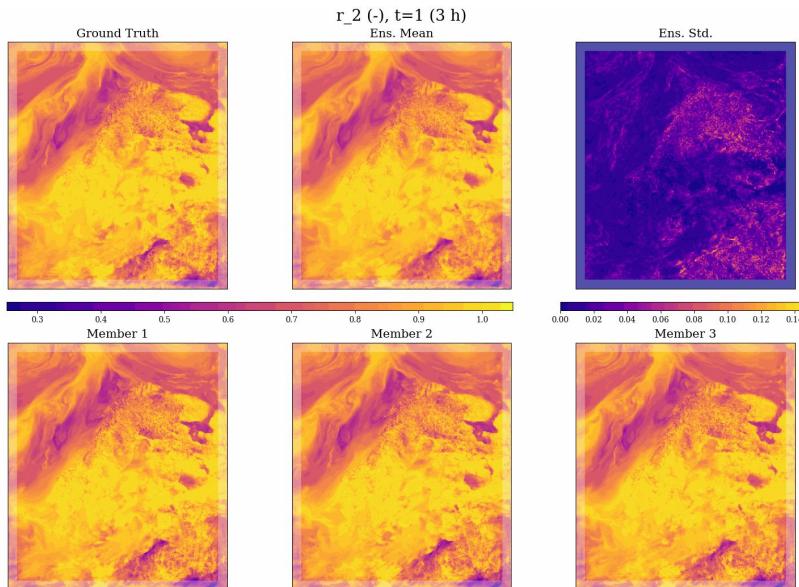
# Case Study Sabine - DANRA

wind\_v\_10m starting at 2020-02-09 - 12 UTC



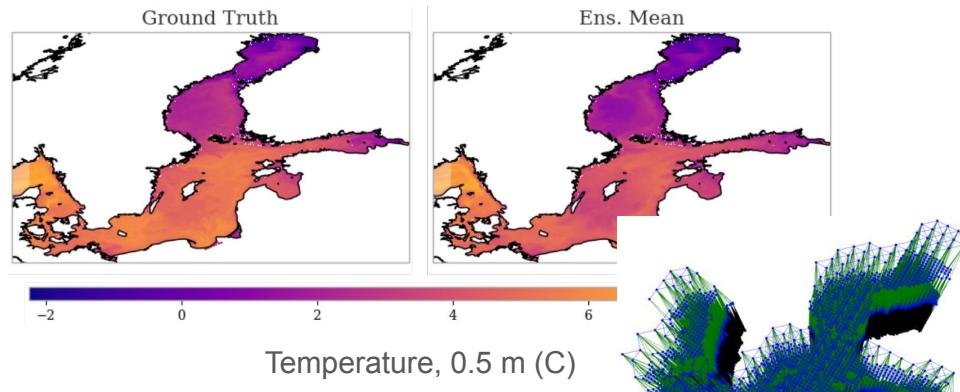
# Outlook

## Probabilistic LAMs<sup>1</sup>



## Regional Earth System Models

- Oceanography<sup>2</sup>



<sup>2</sup> D. Holmberg, et al. (2025). Accurate Mediterranean Sea forecasting via graph-based deep learning. Preprint. + Ongoing work.

<sup>1</sup> J. Oskarsson, et al. (2024). Probabilistic Weather Forecasting with Hierarchical Graph Neural Networks. NeurIPS.

E. Larsson, et al. (2025). Diffusion-LAM: Probabilistic Limited Area Weather Forecasting with Diffusion. CCAI Workshop @ ICLR.

J. Pathak, et al. (2024). Kilometer-scale convection allowing model emulation using generative diffusion modeling. Preprint.

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Realistic Settings

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**Joel Oskarsson** (LiU)

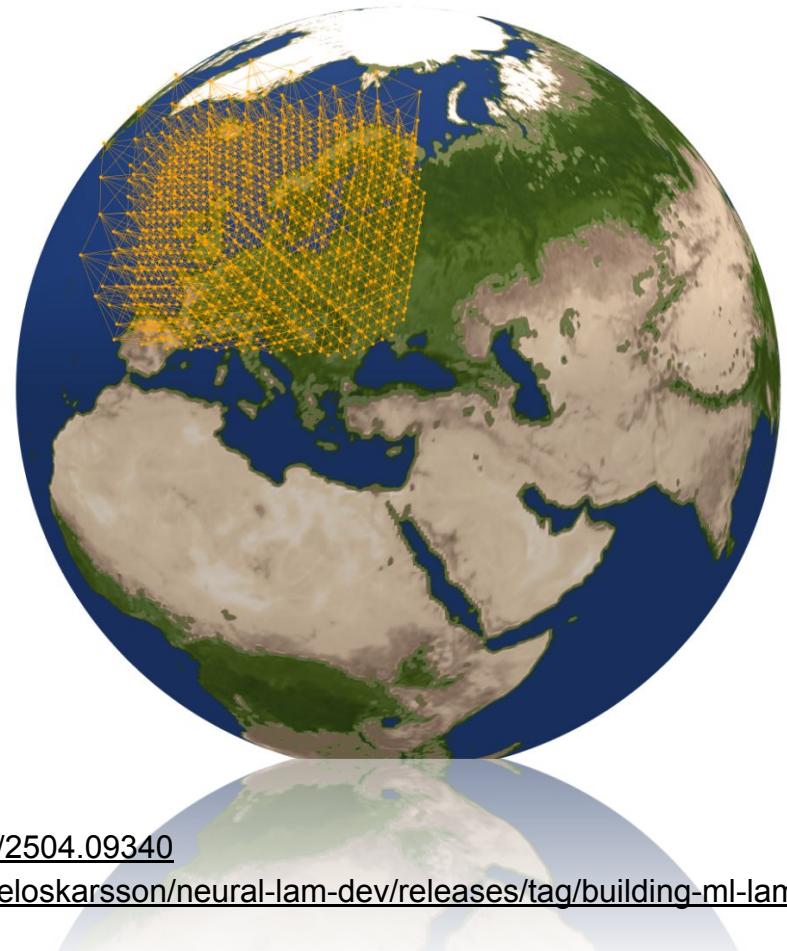
## Co-authors:

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Irene Schicker (GeoSphere)  
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Sebastian Schemm (ETH, Cambridge)

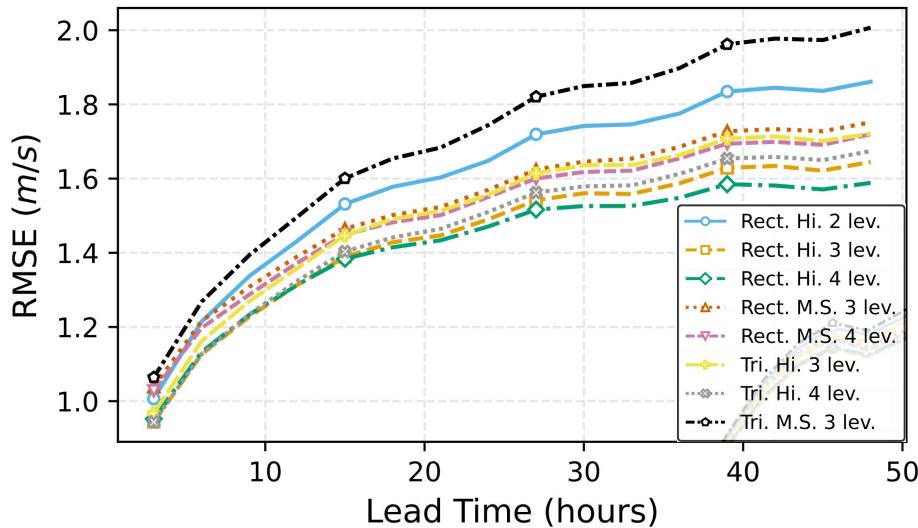


Paper: <https://arxiv.org/abs/2504.09340>

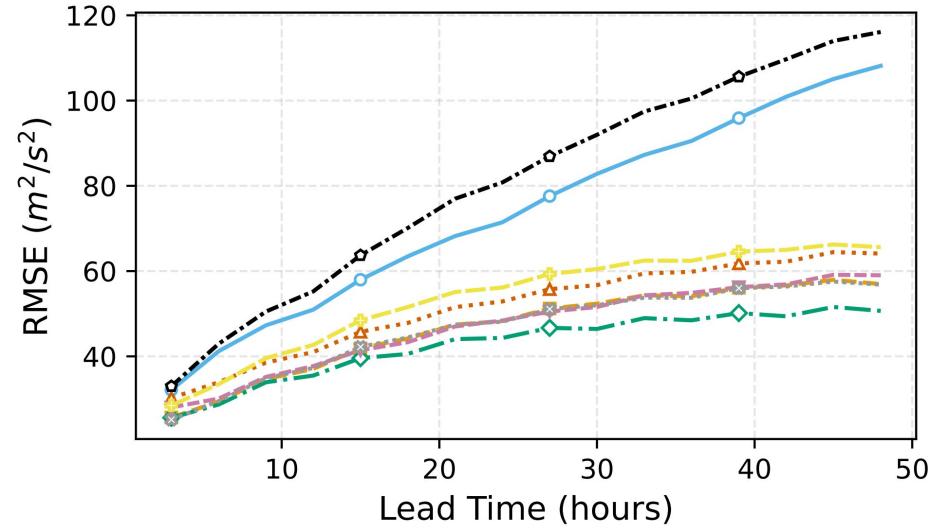
Code: <https://github.com/joeloskarsson/neural-lam-dev/releases/tag/building-ml-lams>



# Design Studies - Graph Design - DANRA



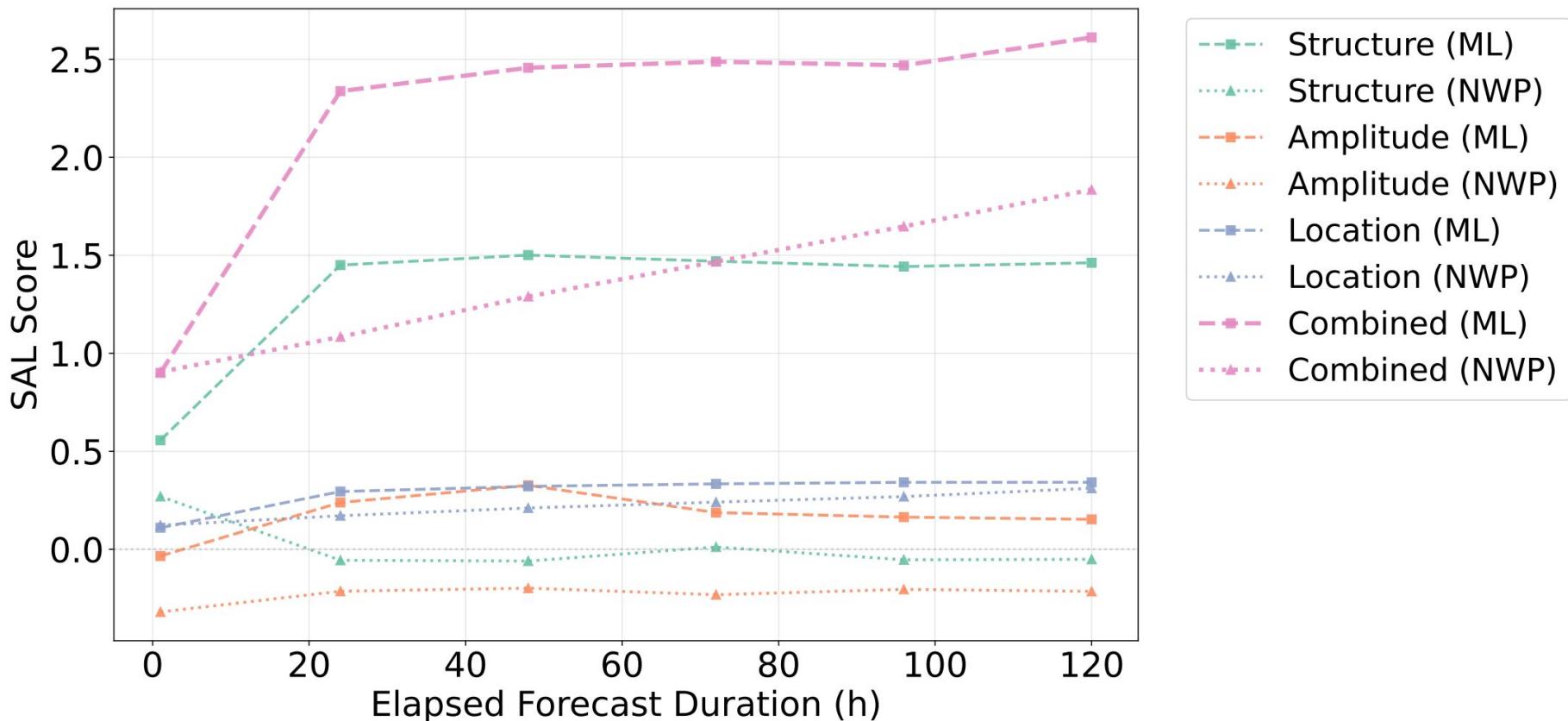
(b) 10 m wind



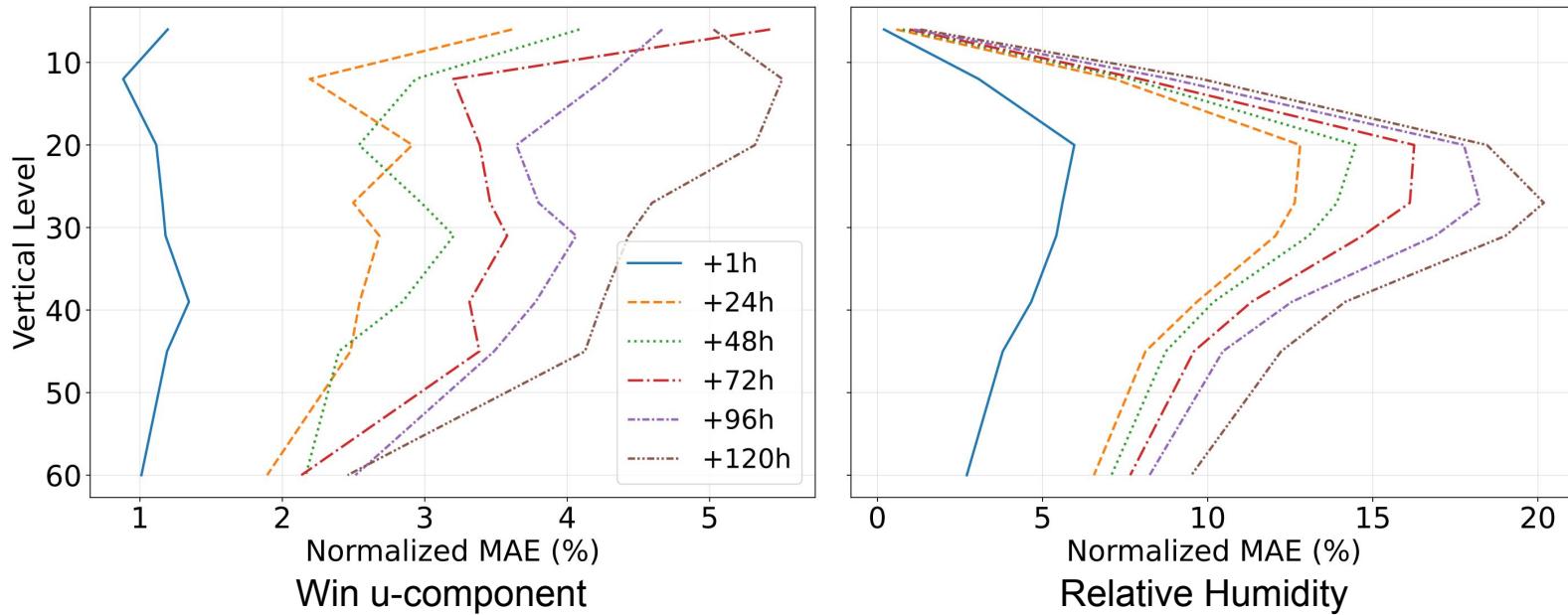
(d) Geopotential at 600 hPa ( $z 600$ )

4-level hierarchical rectangular graph slightly outperforms the others

# Verification Gridded - Precipitation - COSMO



# Verification Gridded - Vertical Profiles



Shown are forecasts for COSMO - DANRA is more balanced

- Model performs worse in the upper atmosphere
- Loss weights can be adjusted

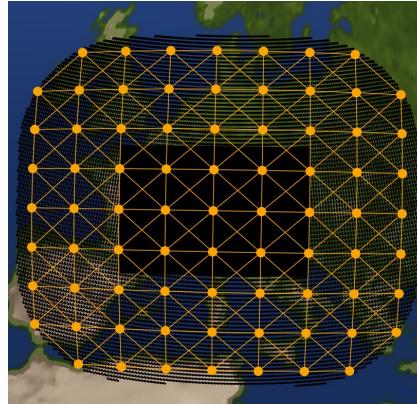
# HPC Resources

<b>Configuration</b>	<b>DANRA</b>	<b>COSMO</b>
Dataset size (time steps)	54,896	33,660
GPU Type	NVIDIA A100/H100	NVIDIA GH200
Total GPUs per run	16	256 (H100s)
<b>Pre-training Phase</b>		
Epochs	80	200
Autoregressive rollout steps	1	1
Average training time [h]	144	12
Total GPU hours	2,304	3,072
<b>Fine-tuning Phase</b>		
Epochs	3	50
Autoregressive rollout steps	4	4*
Average training time [h]	36	14
Total GPU hours	576	3,584
<b>Number of Trainings</b>		
Pre-training	12	9
Fine-tuning	12	12
<b>Total GPU-hours</b>		34,560
		70,656

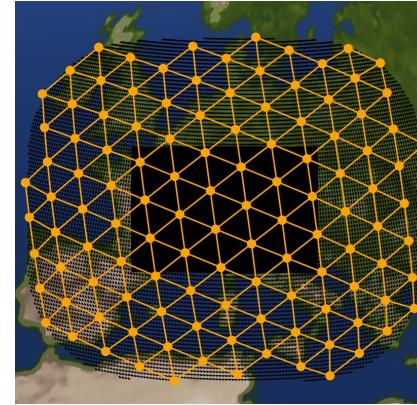
# Graph design

Multi-scale

Rectangular



Triangular



Hierarchical

