

AICON – Introducing ML-based weather forecasting at DWD

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ECMWF Workshop on HPC | 17 September 2025



Warm Up: Context & Goals

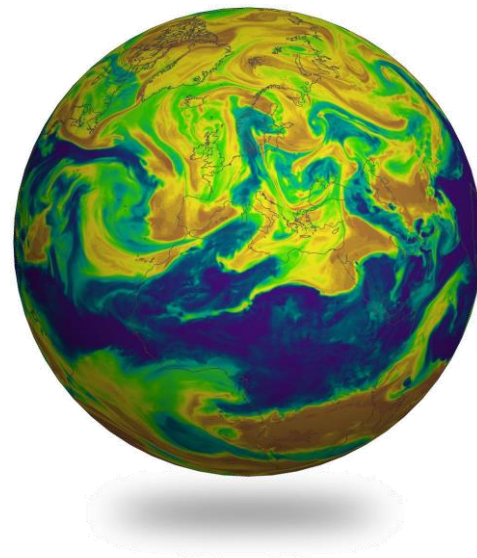
Substantial progress in the realm of data-driven weather forecasting: *FourCastNet*, *Pangu-Weather*, *GraphCast*, *GenCast*, *Aurora* (NVIDIA/Huawei/Google Deepmind, Microsoft), ...

DWD numerical weather prediction: ML-based forecasts as a complement to global and regional **ICON model**.

Operational NWP System AICON-Global

Current status (2025-09-03): AI-based forecasts provided for evaluation, research, and training. Complements but does not replace the current operational model, forecast skill is still evolving.

Example of an AICON-Global forecast for specific humidity at the respective ICON vertical level 101



Source: 2025-09-03, Operationelles
NWV-System Änderungsmitteilung

The Anemoi Framework



Anemoi

Python-based toolkit for data-driven models

Github: <https://github.com/ecmwf/anemoi-core>



PyTorch Lightning



PyG



xarray



earthkit



<https://events.ecmwf.int/event/410>



Lang, S., Alexe, M., Chantry, M., Dramsch, J., Pinault, F., Raoult, B., Clare, M. C. A., Lessig, C., Maier-Gerber, M., Magnusson, L., Ben Bouallègue, Z., Prieto Nemesio, A., Dueben, P. D., Brown, A., Pappenberger, F., & Rabier, F. (2024). AIFS -- ECMWF's data-driven forecasting system. arXiv.

<https://doi.org/10.48550/arXiv.2406.01465>

Nipen, T. N., Haugen, H. H., Ingstad, M. S., Nordhagen, E. M., Salihi, A. F., Tedesco, P., Seierstad, I. A., Kristiansen, J., Lang, S., Alexe, M., Dramsch, J., Raoult, B., Mertes, G., & Chantry, M. (2024). Regional data-driven weather modeling with a global stretched-grid [Preprint]. arXiv.

<https://doi.org/10.48550/arXiv.2409.02891>



The Anemoi Framework

Collaborative European initiative

- Anemoi plays a key role in the development of multiple ML-powered weather models:
AIFS (Artificial Intelligence Forecasting System, ECMWF),
Bris (MetNorway, extends the AIFS) and **AICON** (DWD).
- DWD abandoned its in-house development in June 2024 in favor of the shared Anemoi codebase.
- The Anemoi Framework received the EMS Technology Achievement Award 2025.
- Development related to EUMETNET E-AI: Artificial Intelligence and Machine Learning in Weather, Climate and Environmental Application



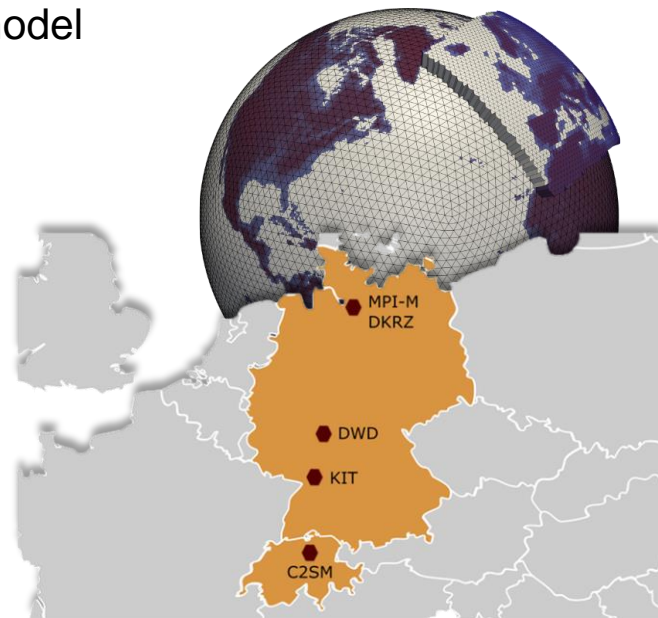
ICON Model

ICOsahedral Nonhydrostatic: global and regional grid point model

- numerical grid point model, developed 2004 – today
- in operational production at DWD since 2015
- applicability on a wide range of scales from ~100km to ~100m, local mass conservation, tracer air-mass consistency

Duration of a deterministic 180h ICON run: 50 min
48 VE nodes NEC SX Aurora 1

see the ICON talk by Uli Schättler,
Thursday, 18 September!



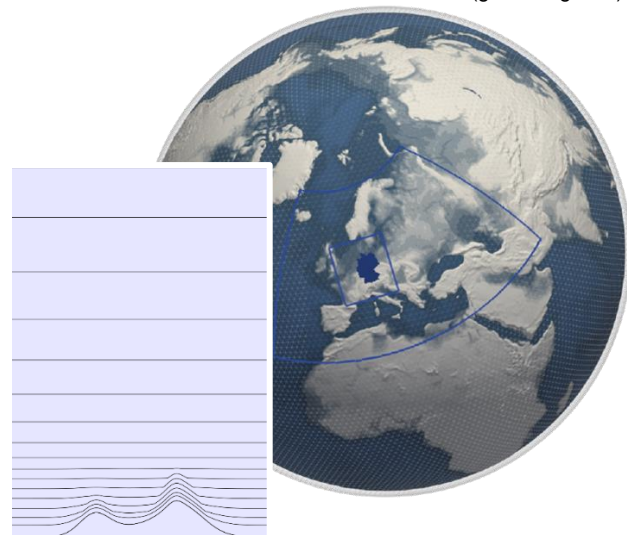
ICON Reanalysis Dataset

The data-driven AICON-Global is based on the ICON reanalysis dataset

ICON DREAM = Dual resolution Reanalysis for Emulators, Applications and Monitoring

- 13 km mesh, 2,949,120 horizontal data points
- (current) reanalysis time range: 2010-01 until 2025-04
- storage size of dataset: 6.45 PB
- 2 km regional reanalysis: currently work in progress
- no release yet; a service is planned for 2026

Operational ICON domains
(global/regional)



Ref.: ICON-DREAM: A new dual resolution reanalysis from DWD. 6th WCRP International Conference on Reanalysis. (2024). <https://confit.atlas.jp/guide/event/icr6/subject/OR2-01/detail> (A. Valmassoi et al., DWD)

ICON Smooth Level Vertical
(SLEVE) coordinate;
Note: different from ERA5
reanalysis dataset with (hybrid
sigma-)pressure levels!

AICON Model Architecture

Reduced-level Zarr dataset: 29.5 TB

prognostic

```
PS, P[:,], T[:,], U[:,], V[:,], QV[:,], T_2M, U_10M, V_10M, QV_S, RELHUM_2M, T_G, ALB_RAD,  
H_SNOW, SMI[0/1], T_SO[0/1],
```

forcings:

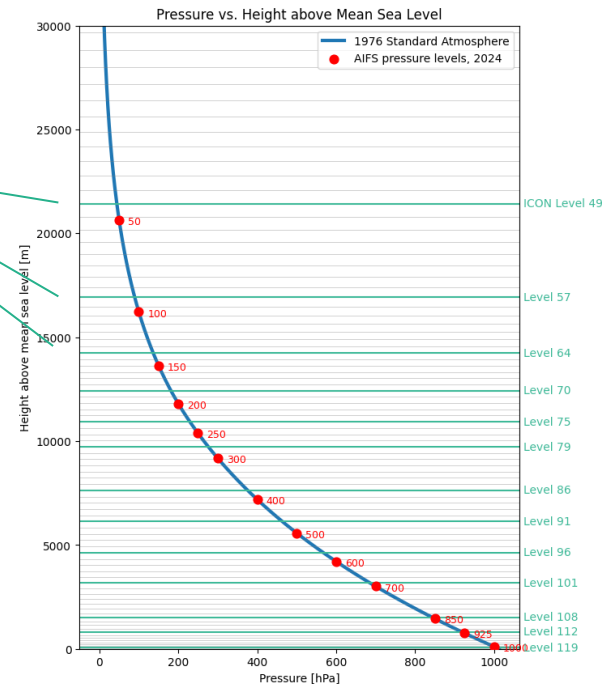
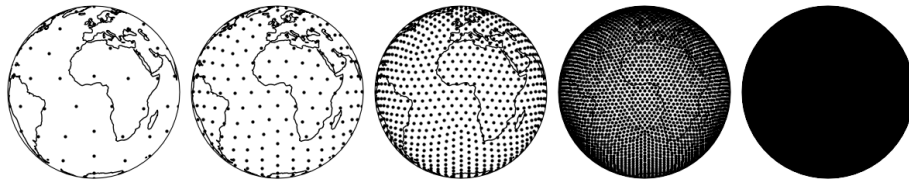
```
HSURF, FR_LAND, Z0, FR_LAKE, EMIS_RAD, SSO_STDH, cos/sin_latitude/longitude,  
cos/sin_julian_day, cos/sin_local_time, insolation
```

13 ICON levels (top-down ordering):
49, 57, 64, 70, 75, 79, 86, 91, 96,
101, 108, 112, 119

diagnostic:

TOT_PREC

ICON data locations are based on cell centers of a triangular grid.
Grid generation inherently defines hierarchical decompositions:



AICON Model Architecture (cont'd)

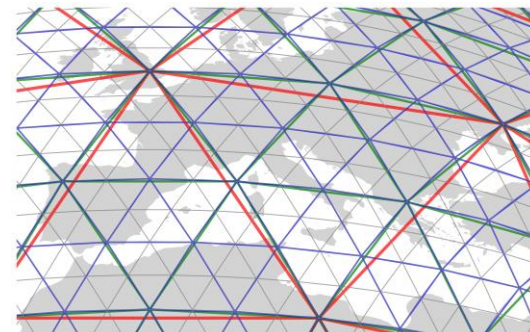
GraphCast-like encoder-processor-decoder architecture.

encoder: maps onto a hidden state

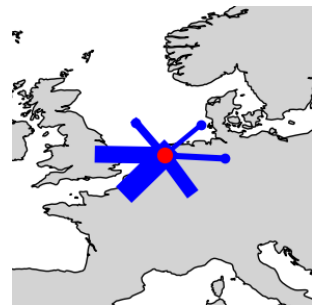
processor: contains latent information

decoder: takes final hidden state

- Graph construction directly based on ICON's triangular meshes.
- **Graph-Transformer GNN:** Message passing is done via a multi-head attention mechanism. Each node's new features become a weighted average of its neighbors' features.



Processor: Different levels of refinement facilitate communication at different scales.



Ex.: Attention graph, relative importance of a neighbor to a target node.

Verification Results

- AICON at 13 km icosahedral grid

training.start: 2010-01-01T00:00:00

training.end: 2023-12-31T21:00:00

frequency: 3h, training without rollout

- Verification against SYNOP observations

- AICON vs ICON. Color coding:

- Green: AICON better

- Red: ICON better

- Good near-surface forecast skill for short range (0 – 72 hrs)

Anemoi version: anemoi-models==0.5.0

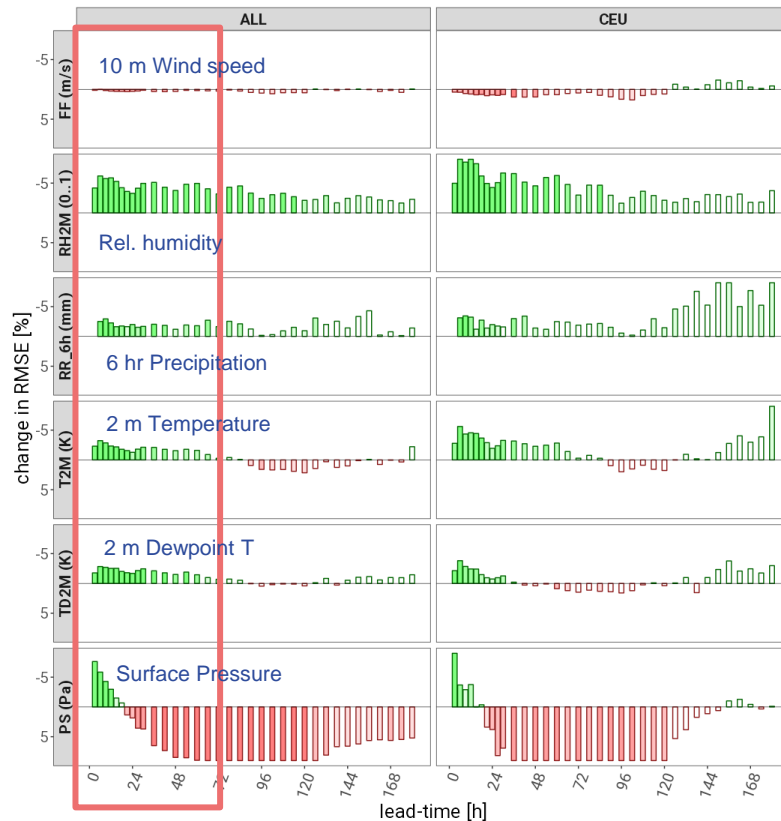
inference checkpoint 89887843679d47deac1b82be5ef7ffc3



Forecasts valid from 2025/08/01 to 2025/08/31

Reduction of RMSE [%], INI; 00, 03, 06, 09, 12, 15, 18, 21UTC, SIGTEST

■ AICONP1 better ■ ICON better Significance 0.00 0.25 0.50 0.75 1.

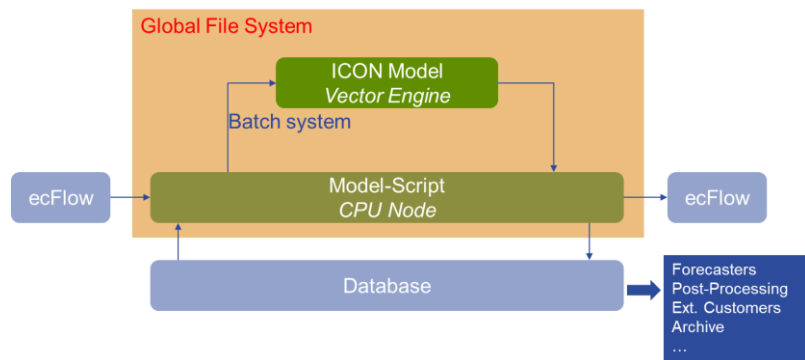


Plot: Marek Jacob, Felix Fundel, DWD

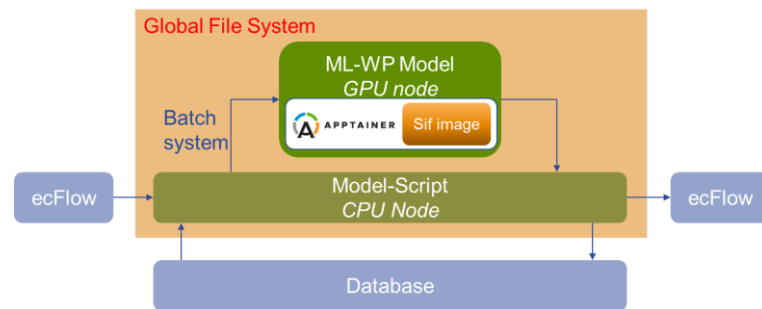
Production Environment

AICon fits seamlessly into the existing process chain of 24/7 numerical weather forecasting.

DWD classical NWP process chain



ML-model process chain



(M. Jacob, DWD)

Containerized multi-GPU inference

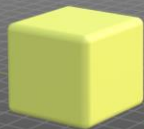
- straight deployment into production environment: base layer for Pytorch, Eccodes
- incl. pre-processing (e.g. SMI), post-processing (lat-lon interpolation, clipping)



Duration/energy estimate of a deterministic ICON global run (13 km)

deterministic ICON global run
energy consumption: 60.24 kWh
~ 21.87 kg CO₂ emission¹

AICON inference
energy consumption: 0.13 kWh
~ 48.28 g CO₂ emission



¹ CO₂ emissions based on German electricity mix (as of 2023/2024)

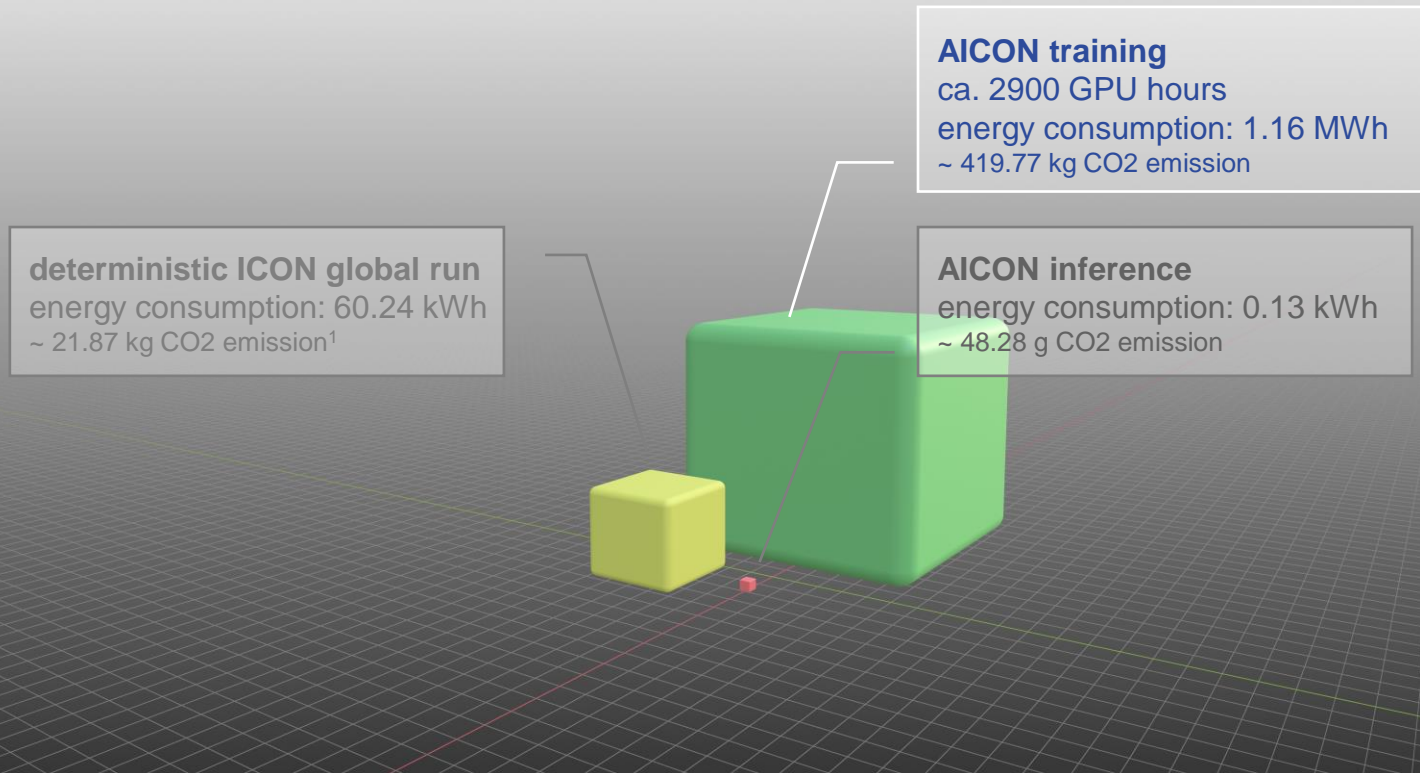
Details

180h lead time

GPU: A100-80, 400W

SX Aurora 1: avg. 1480W

Energy Statistics



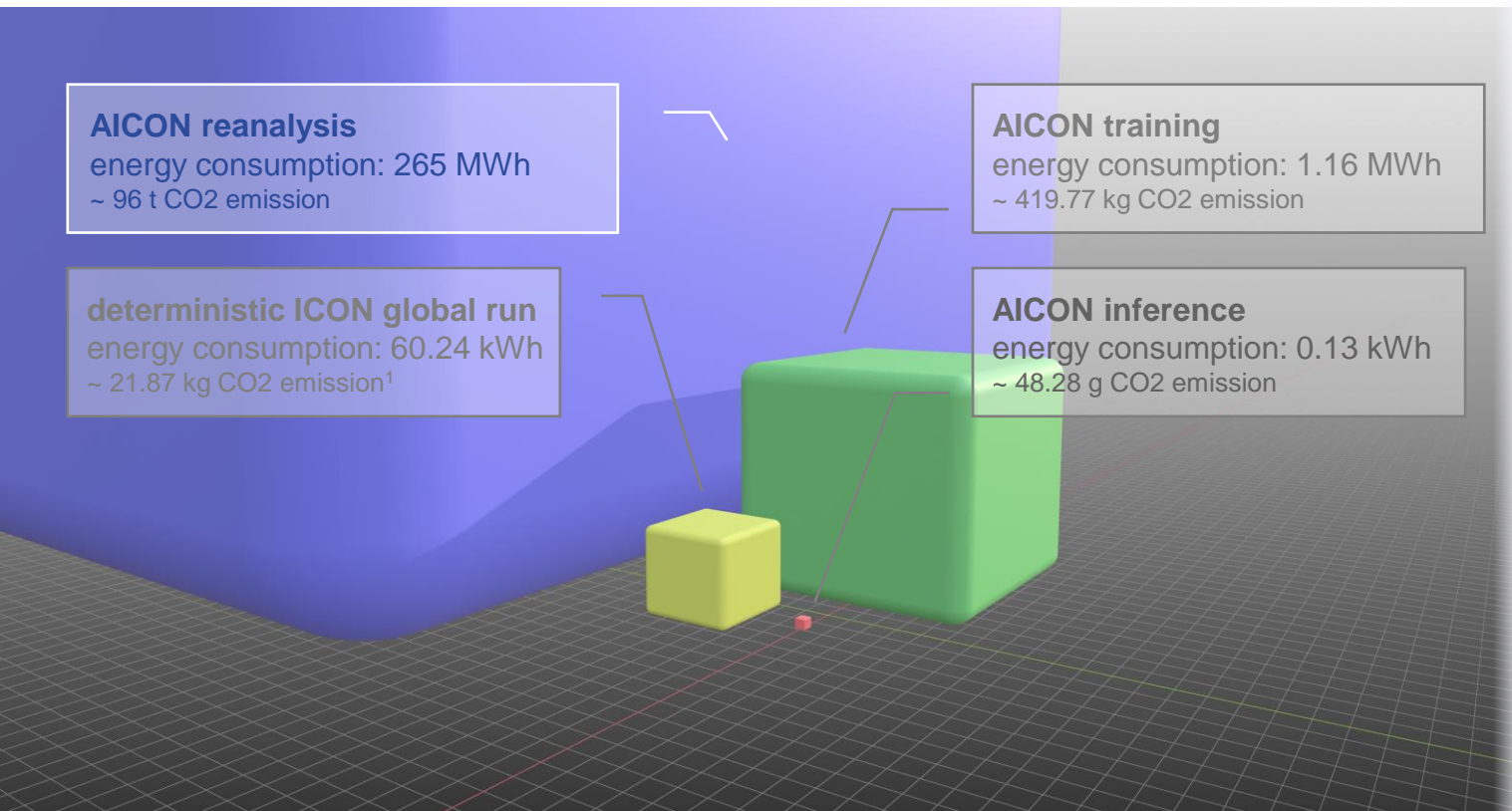
Model has a relatively low training cost.

For comparison:
Llama 2-7B training

184,320 GPU hours,
hardware: A100-80G

(<https://arxiv.org/abs/2307.09288>)

Energy Statistics

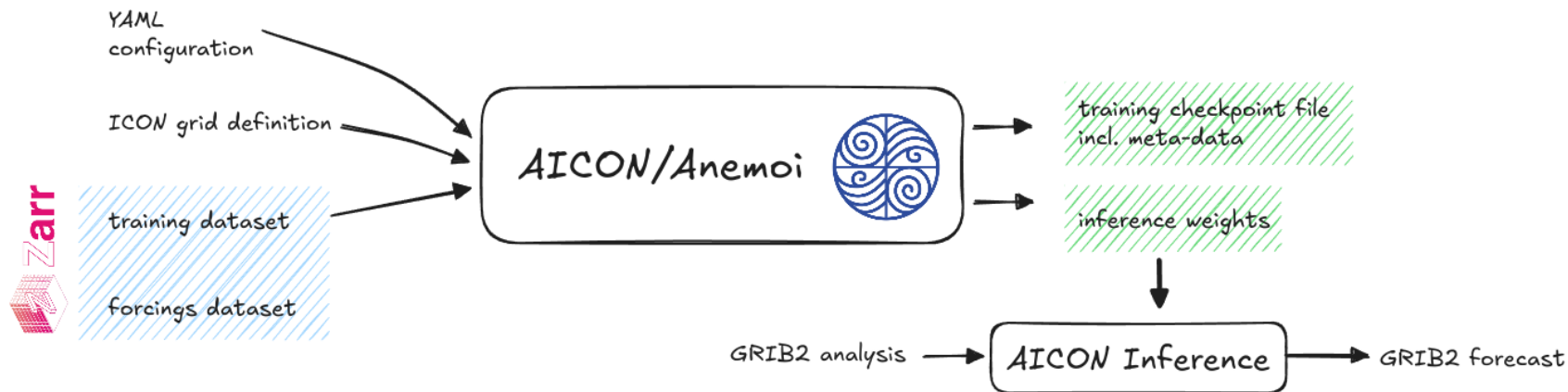


Details

Reanalysis
deterministic, global,
2010-01 until 2025-04

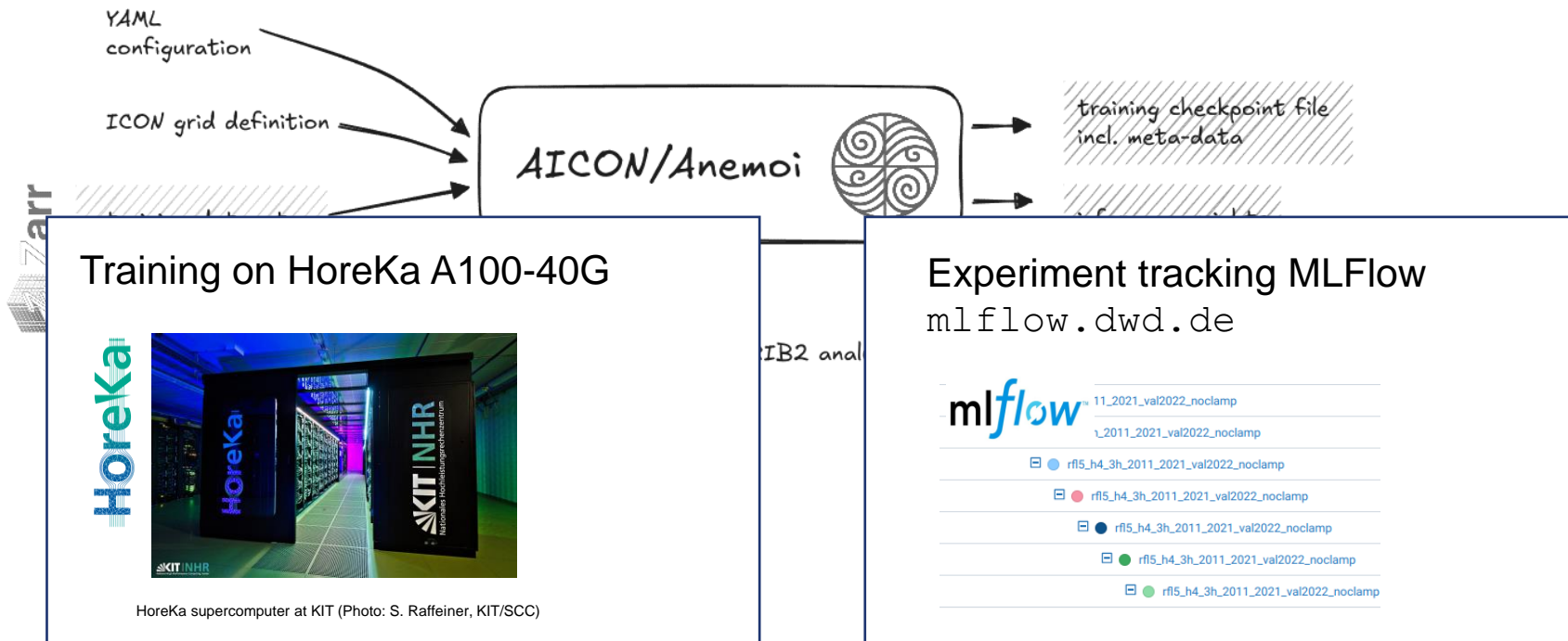
(currently on-going,
including back-extension)

Training Environment



Transfer learning between mesh resolutions: organization of a cost-efficient training schedule as long as higher resolution training graphs preserve the essential structural and statistical properties: **53 km → 26 km → 13 km**

Training Environment



“New HPC”

Training & inference: contrast to current (almost symmetric) hardware configuration.

- NEC SX-Aurora TSUBASA Vector Engine,
- Top500 list June 2025 theoretical peak performance
position 113: 16.43 Rpeak (PFlop/s) /
position 156: 12.22

asymmetry ratio = 1.34

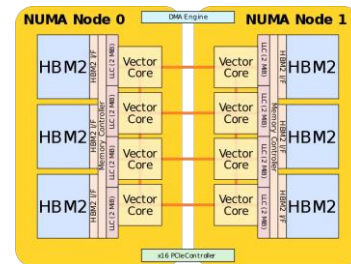


NEC SX-Aurora rack mount model

Is there a way to make use of existing hardware, originally targeted at grid point models?

Inference: Utilization of the existing vector HPC?

SX-Aurora: Vector processors on PCIe-based accelerator cards with high-bandwidth memory on-chip



<https://en.wikichip.org/wiki/nec/microarchitectures/sx-aurora>

AI Compiler NEC SOL

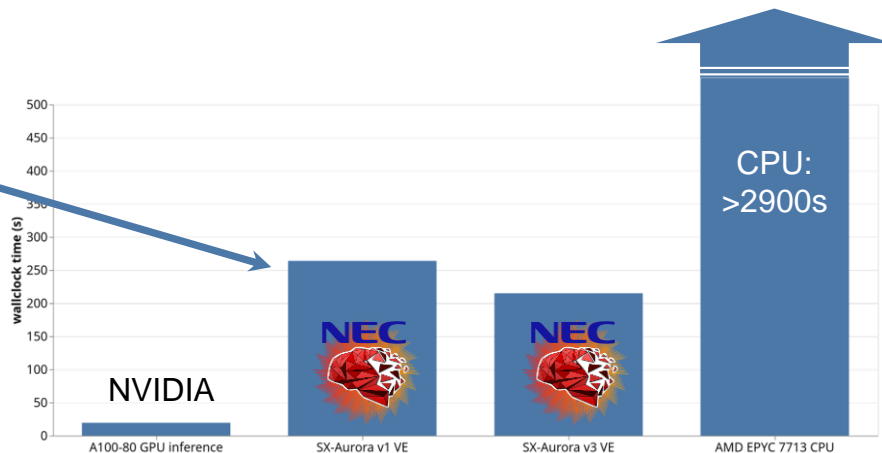
Proof-of-concept: AICON runs on NEC Vector Engine (VE)!

- Only very minor adjustments to the inference code are necessary (essentially `import sol; sol.device.set('ve', 0)`).
- Currently: VE uses 16 cores, but only 1 VE.



But: GPU has a significant(10x) advantage!

- only needs to read 50% of the memory for the model parameters and can still use its TensorCores for `torch.float16`.
- GPU can make use of its atomic read-modify-write operations



Acknowledgments:
Many thanks to
Nicolas Weber @ NEC

Work in Progress



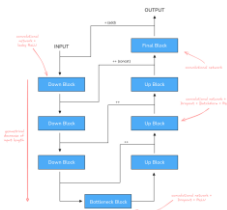
anemoi

1D Vertical Super-Resolution

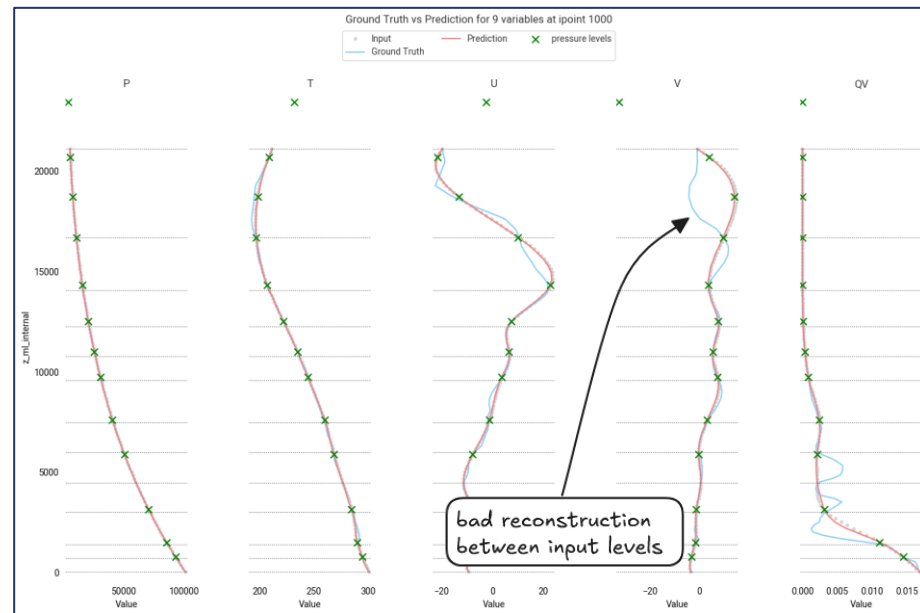
AICON predicts a comparably small number of vertical levels.

Column-wise offline technique:

- pre-upsampling super-resolution model: the low-resolution model output is first upsampled to the target high-resolution size using a traditional interpolation method.
- Convolutional neural network then learns to improve and refine the upsampled data.



da Silva Rodrigues, J. D., & Morcrette, C. J. (2025). Improving vertical detail in simulated temperature and humidity data using machine learning. *Atmospheric Science Letters*, 26(2), e1288. <https://doi.org/10.1002/asl.1288>



Ex.: ICON data, ML-based reconstruction of vertical profile.

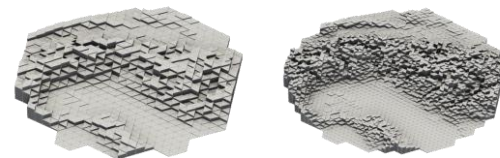
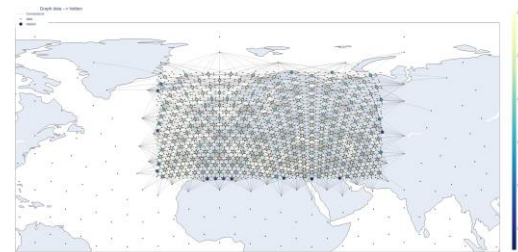
AICON Limited Area Model

Work in progress (Sabrina Wahl et al., DWD)

Merge global and regional input datasets.

- Regional reanalysis ~6.5 km EU nest.
- Overlay the regional dataset t+0h with the global dataset t+3h.
- Global input at boundaries and inside the domain, encoder edges from the sets of global and regional data nodes.
- Processor: multi-mesh over the LAM region.

... different from “stretched-grid model approach” where global grid points that overlap with the regional model are removed (Nipen et al. 2024: <https://arxiv.org/abs/2409.01891>).

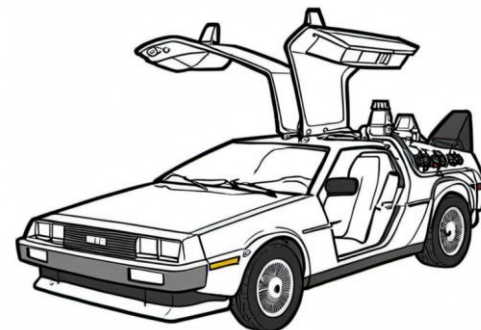


R03B07, 13 km grid R03B08, 6.5 km
ICON, alpine region, ASTER orography

Preparing for Operational Rollout

Plans

- Q3 2025 : AICON (13 km global) technically operational for validation by the DWD forecast center ✓
- Q2 2026 AICON-LAM (6.5 km EU) in NWP operation (technically operational)
- Q1 2027 AICON-LAM (2 km DE) in NWP operation (technically operational)



- Pain Points and Challenges: physical inconsistencies, clipping needed; higher temporal resolution (1h), adaptability important, ...
- AI-driven data assimilation (AIDA) – not covered here:

Keller, Jan & Potthast, Roland (2024). AI-based data assimilation: Learning the functional of analysis estimation. 10.48550/arXiv.2406.00390.



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