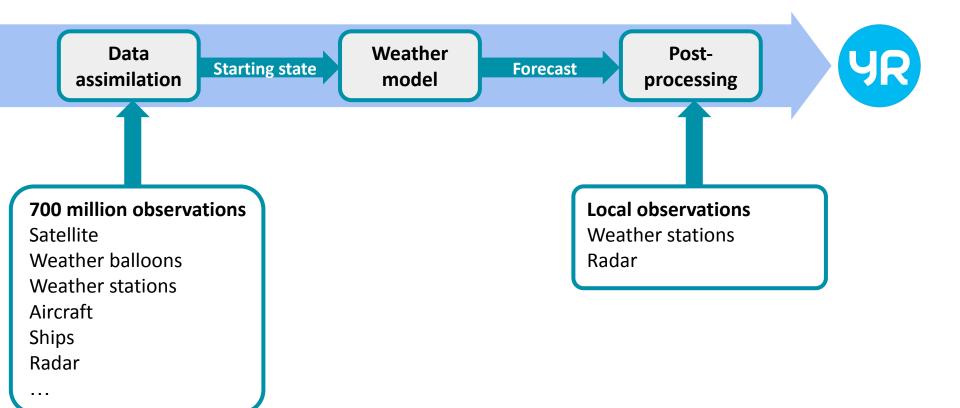
Al in weather forecasting at MET Norway

○ Norwegian Meteorological Nostitute

Thomas Nipen + many colleagues at MET Norway



Fully automated production chain



Data-driven models for NWP

- Several very competitive models have emerged in the last 2 years
- Trained on 40+ years of global reanalysis data (ERA5 at ~31km resolution)
- Training is expensive (~10s of thousands of GPU hours)
- Inference is several orders of magnitude faster than physics-based models

Pangu-weather Huawei	FourCastNet NVIDIA	GraphCast Google
FuXi Fudan University		AIFS ECMWF
Vision transformer	Fourier neural operator	Graph neural network

Data-driven models for NWP

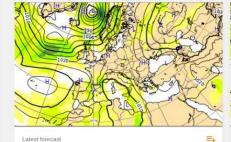
ECMWF | Charts

↑ Home / Charts catalogue

- Q Search products...
- Range
- Medium (15 days)
- Extended (42 days)
- Long (Months)
- Туре
- Forecasts
- Verification
- Component
- Surface
- Atmosphere

Product type

- High resolution forecast (HRES)
- Ensemble forecast (ENS)
- Combined (ENS + HRES)
- Extreme forecast index
- Point-based products
- Experimental: AIFS
- Experimental: Machine learning models



Experimental: AIFS (ECMWF) ML model: Mean sea level pressure and 850 hPa wind speed

AIFS (ECMWF): a deep learning-based system developed by ECMWF. It is initialised with ECMWF HRES analysis. AIFS operates at 0.25° resolution

Latest forecast

Experimental: FourCastNet ML model: Mean sea level pressure and 850 hPa wind speed

FourCastNet v2-small:a deep learning-based system developed by NVIDIA in collaboration with researchers at several US universities. It is initialised with ECMWF HRES analysis. FourCastNet operates at 0.25° resolution.

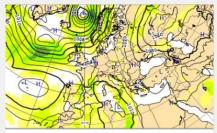
Latest forecast

=+

=+

Experimental: FuXi ML model: Mean sea level pressure and 850 hPa wind speed

FuXi: a deep learning-based system developed by researchers at Fudan University. It is initialised with ECMWF HRES analysis. FuXi operates at 0.25deg resolution.



Experimental: GraphCast ML model: Mean sea

=+

Latest forecast

Latest forecast





😗 Help 🔻 🐳 Log ir

4

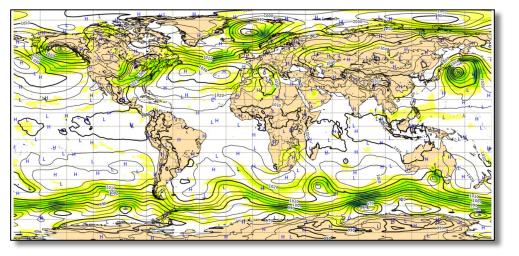
Experimental: Pangu-Weather MI model: Mean Experimental: AIES (ECMWE) MI model: 500 hPa

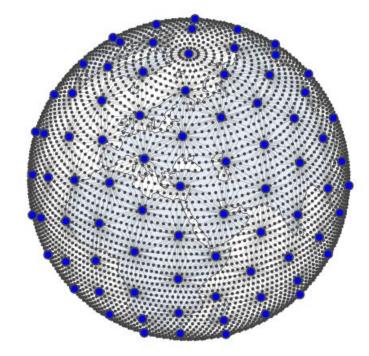
Latest forecast

=+

E.

Graph neural networks for NWP

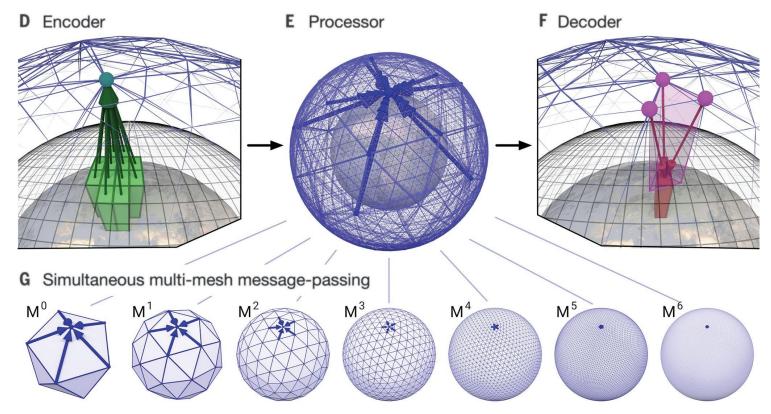




Vision transformer

Graph neural network

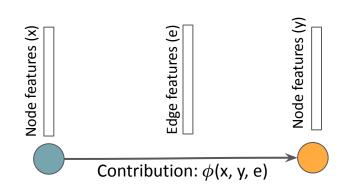
Graph neural networks for weather

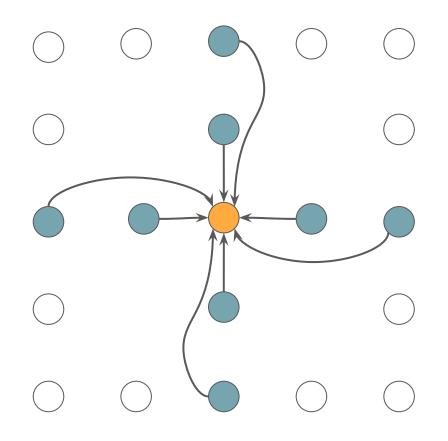


Learning skillful medium-range global weather forecasting https://www.science.org/stoken/author-tokens/ST-1550/full

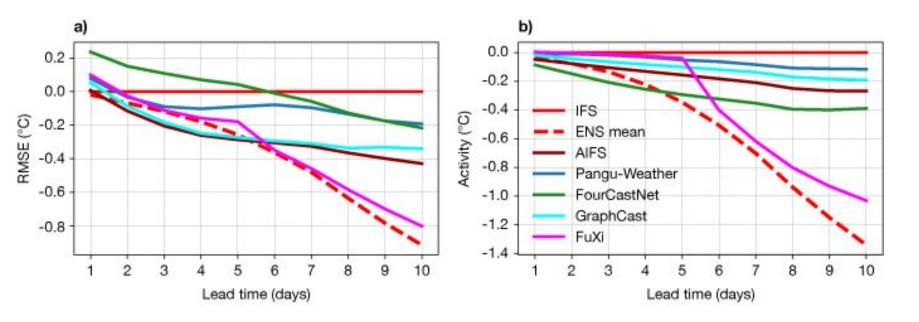
Graph neural networks for weather

- Each neighbour node provides a contribution
- Contributions are aggregated (e.g. summed)





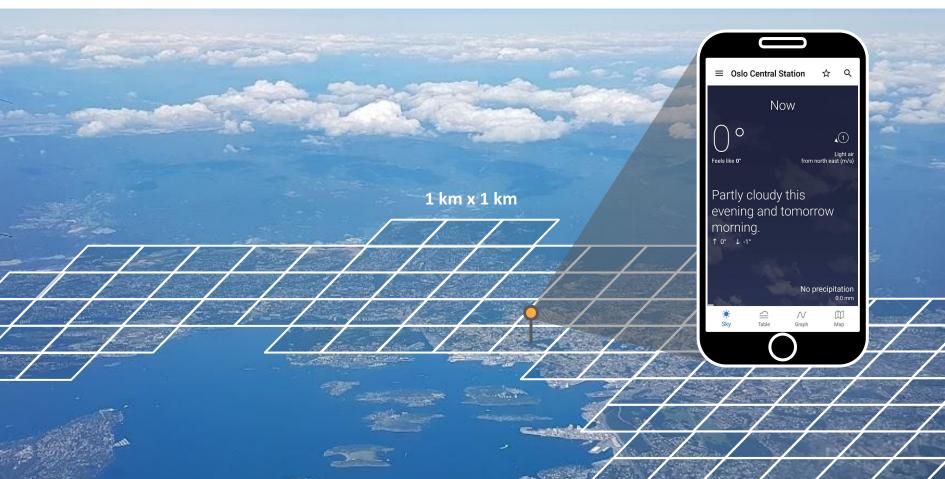
Results



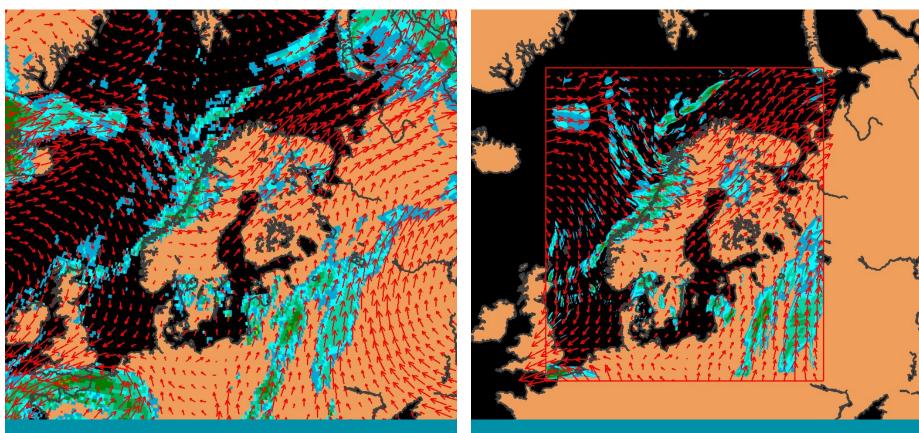
Physics-based reference forecast

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Users expect localized forecasts



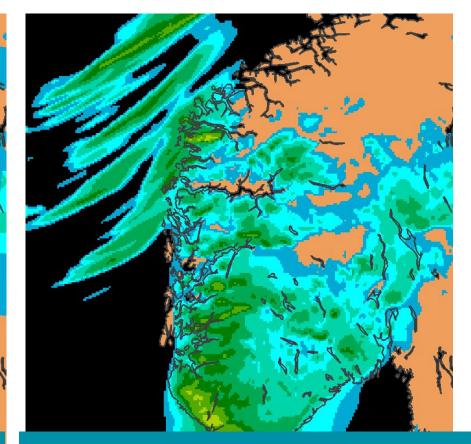
Global vs regional models



Global model (ECMWF IFS)

Regional model (MEPS)

Global vs regional models

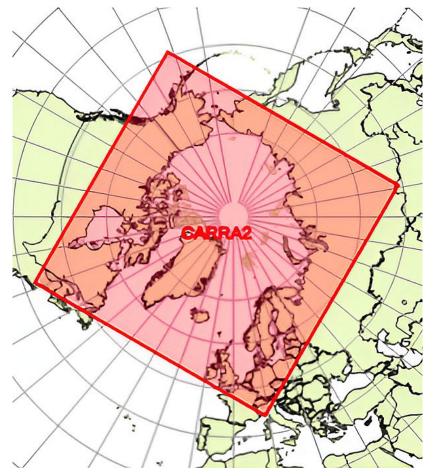


Global model (ECMWF IFS)

Regional model (MEPS)

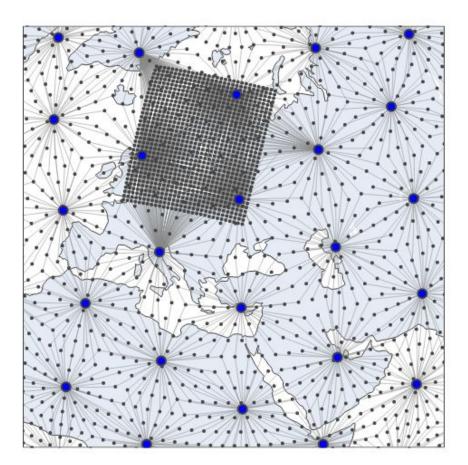
Regional reanalysis datasets

- CARRA2 reanalysis at 2.5 km resolution
- Time range: 1991-2025
- Expected completion: Q3 2026
- Allows us to train high-resolution models for Nordic conditions

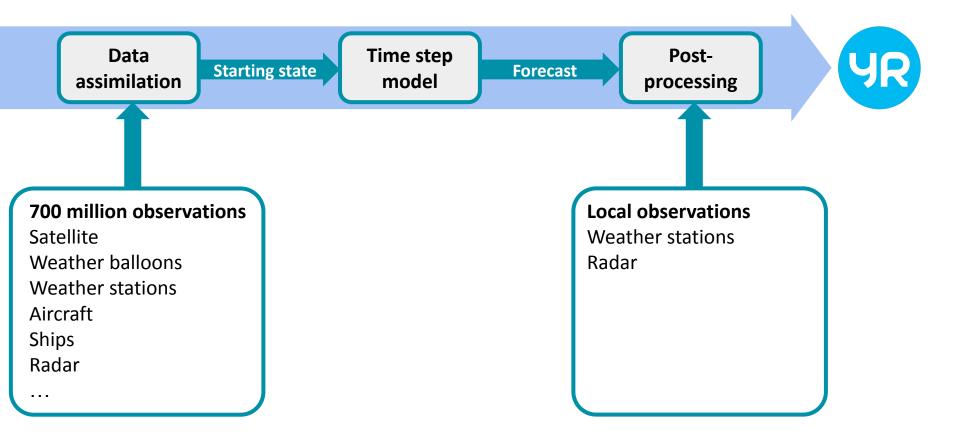


Stretched-grid AIFS

- GNNs allow for arbitrary grid topology
- The grid can be stretched to have higher resolution over the Nordics
- We can combine the initial state from ECMWF's 9 km global model with our own 2.5 km regional model.
- The goal is that a common model learns phenomena at the whole range of scales



Fully automated production chain



Post-processing of temperature

Bias-correction and downscaling of 2.5 km temperature to at 1x1 km resolution

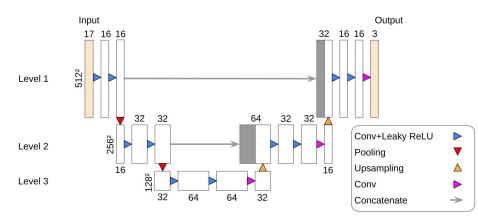
Architecture: U-Net with 6 levels

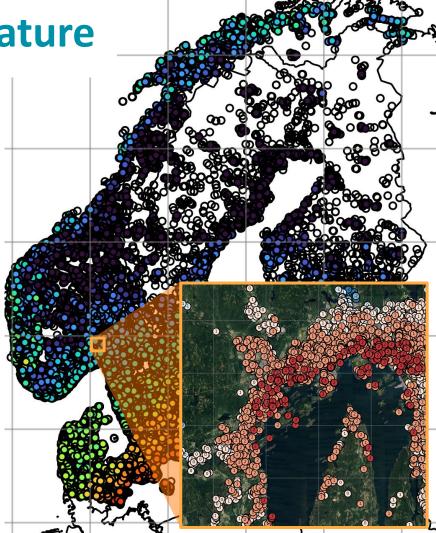
Dataset size: 6TB

Targets: Citizen weather stations (Netatmo)

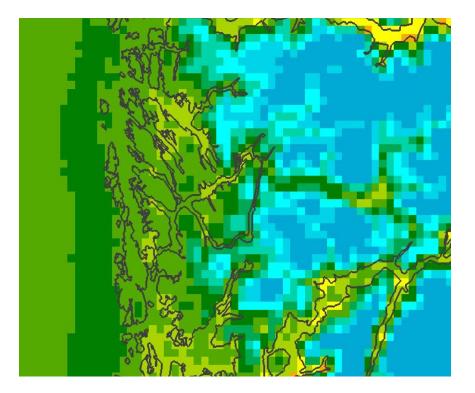
Parameters: 1,314,019

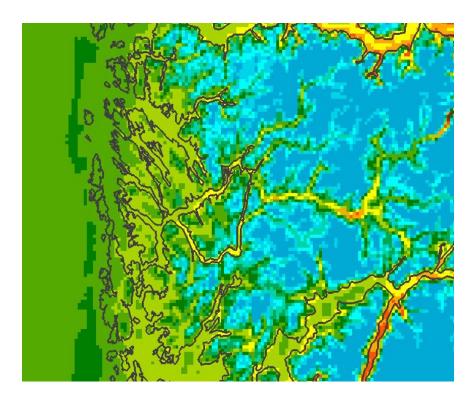
Training time: 12 hours on 4 NVIDIA A-100 GPUs





Post-processing of temperature





2.5 km (NWP model)

1.0 km (NWP+ML model)

Destination Earth projects

On-demand Extremes (DE_330)

- NWP modelling at hectometric resolutions
- Impact models
 - Hydrology, air pollution, renewable energy, ...
- Machine learning components
 - Uncertainty quantification by probabilistic and generative modelling
 - Initial-state models

Machine Learning for Earth system Digital Twins (DE_371)

- Generative machine learning methods for
 - Space-time scenarios of multiple parameters given deterministic forecasts
 - Higher temporal resolution



Emulation of CFD model for turbulence forecasting

Aviation forecasting at 19 Norwegian airports

- Original system
 - MEPS control (2.5 km) \rightarrow CFD model (100 250m)
 - 13 lead times, 2 times/day
- New ML-based system
 - ML models trained separately for each airport
 - relevant variables from MEPS control at model levels (Lambert grid) as input
 - 3D wind and turbulence on 3D grids (rotated spherical) as targets
 - 18 lead times, 8 times/day
 - o computationally cheap
 - \circ in operation from June 2023



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Links

- Run data-driven models on your own: <u>https://github.com/ecmwf-lab/ai-models</u>
- ECMWF weather charts: https://charts.ecmwf.int/
- Open data from MET Norway: <u>https://thredds.met.no/</u>





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Extra slides

Post-processing of temperature

