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How ML is transforming our approach to seamless weather forecasting

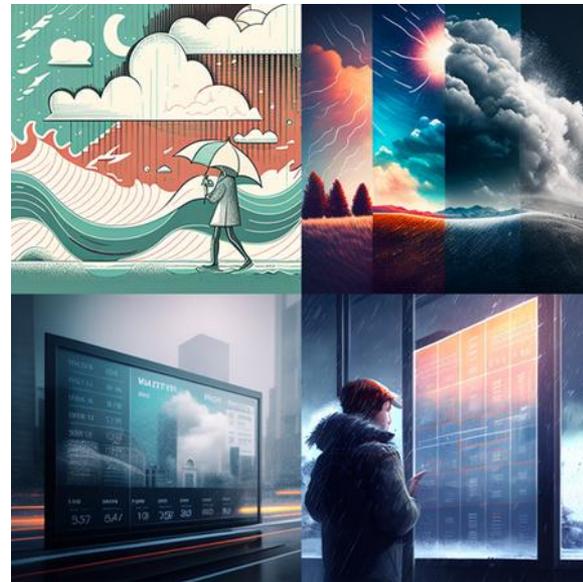
PrePEP Conference, Seamless Prediction
Bonn, 19.03.2025

Daniele Nerini

with contributions from

Verena Bessenbacher, Jonas Bhend, Oliver Fuhrer, Ophélie Miralles, Carlos Osuna, Andreas Pauling, Alberio Pennino, Radi Radev, Francesco Zanetta, Ioannis Sideris

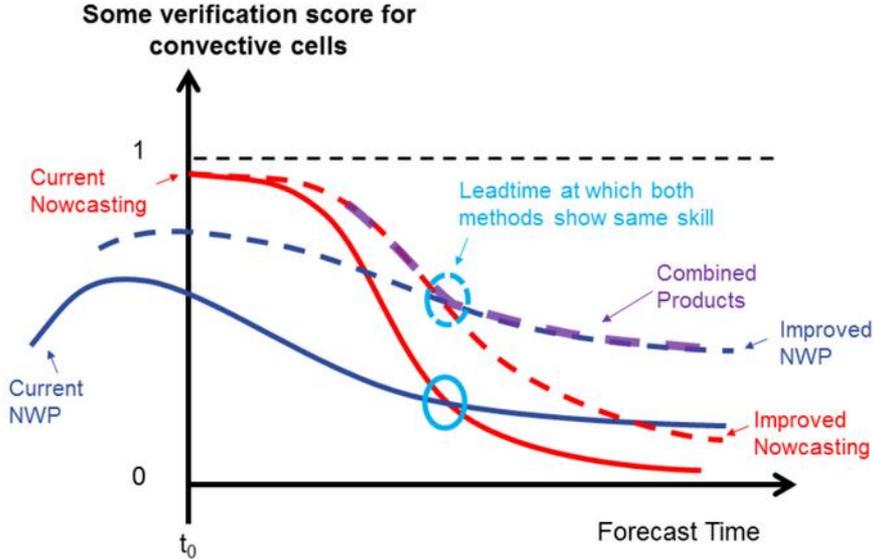
Contact: Daniele.Nerini@meteoswiss.ch





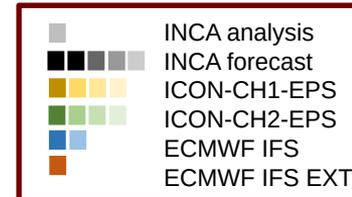
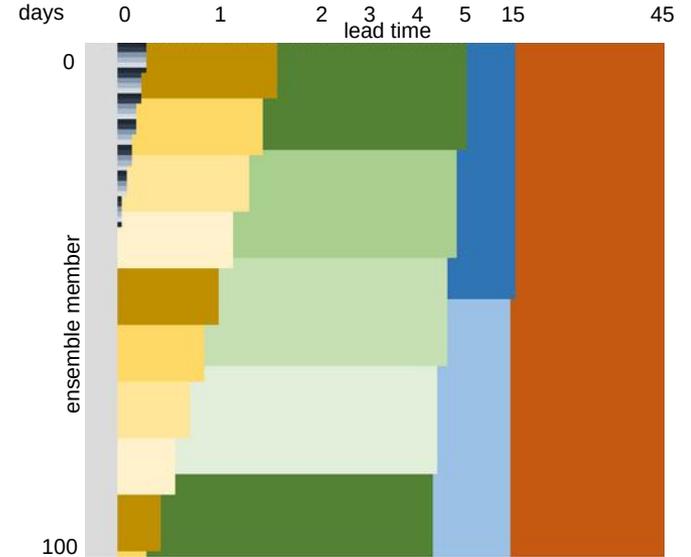
How to Seamless

Basic concept of SINFONY



Source:
https://www.dwd.de/DE/forschung/forschungsprogramme/sinfony_iafe/sinfony_node.html

“Full-stack” seamless forecast





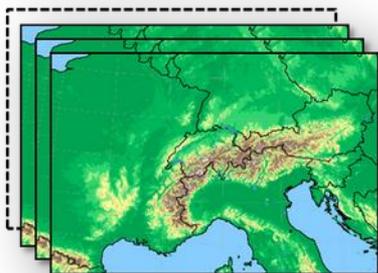
Improving NWP



ICON-CH1-EPS und ICON-CH2-EPS

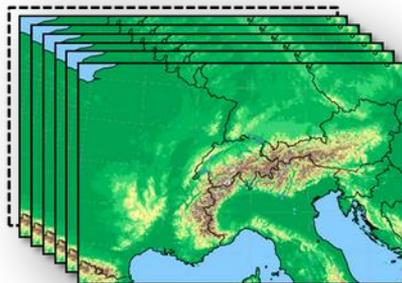
ICON-CH1-EPS

33 hour forecasts, 8x per day
1.1 km grid size
11 ensemble members

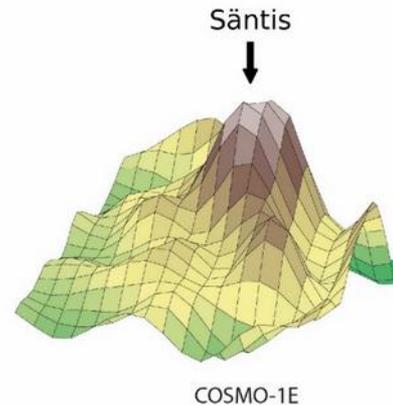


ICON-CH2-EPS

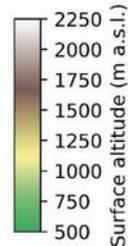
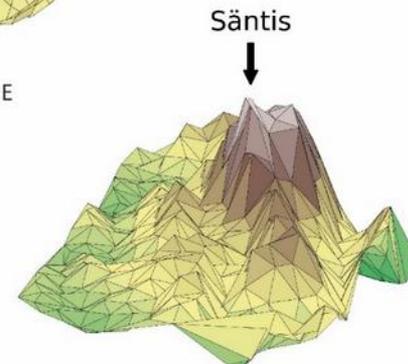
5 day forecasts, 4x per day
2.2 km grid size
21 ensemble members



3-8x in compute capacity would be needed
for running ICON @ 500m !



Same grid resolution, but
more accurate topography



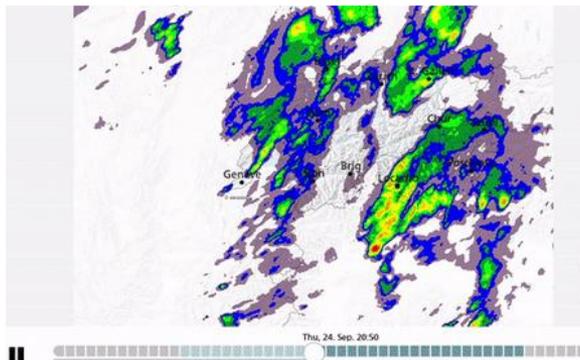


Improving nowcasting

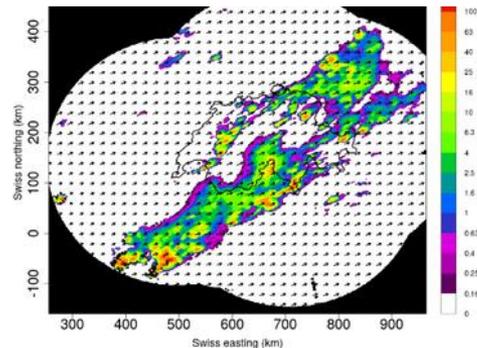
- Nowprecip is MeteoSwiss' operational precipitation nowcasting system.
- 10min / 1km res, +6 hrs
- Nowprecip =

radar extrapolation
+ stochastic perturbations
+ tendency from NWP

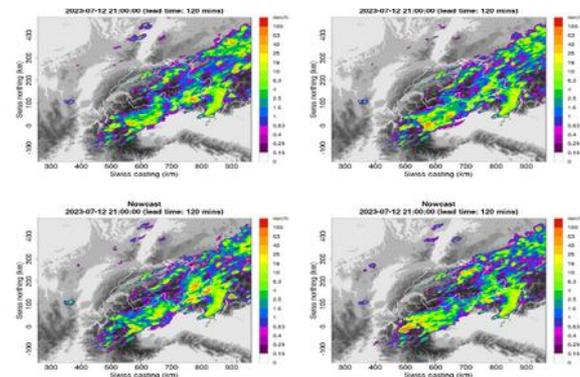
Realistic and seamless



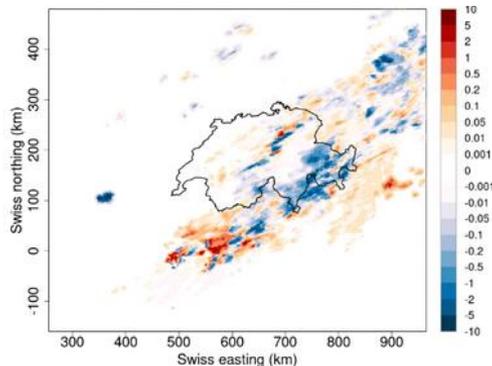
Optical flow



Ensemble



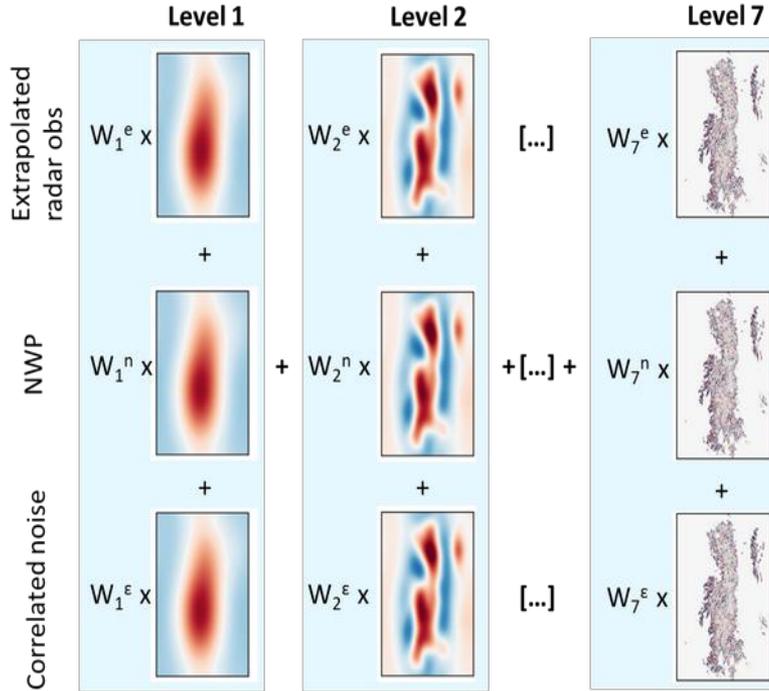
Growth-decay maps





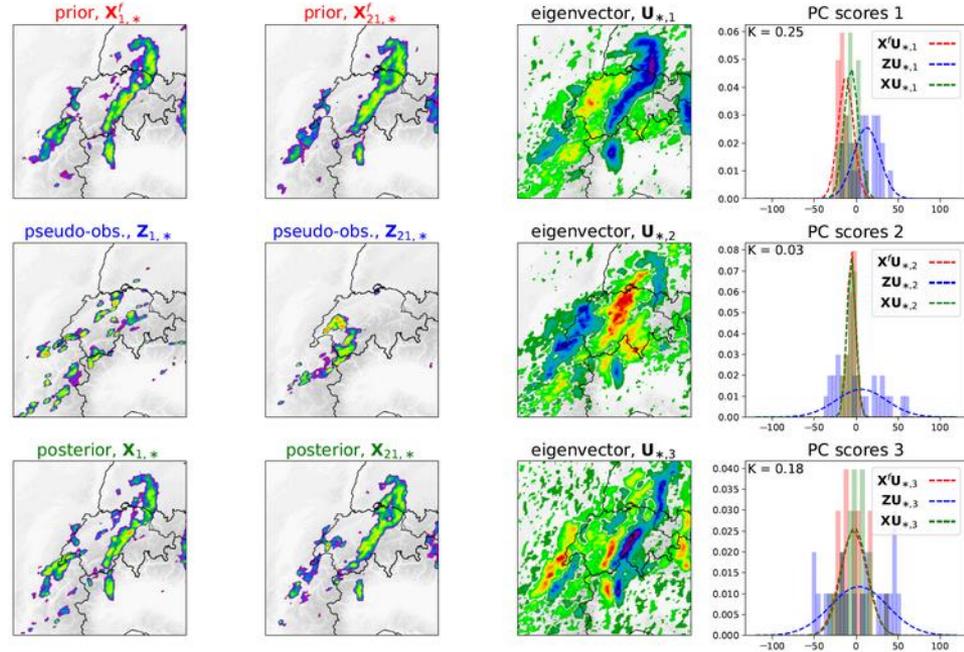
Improving blending

Scale dependent (STEPS)



Imhoff et al. (QJRM, 2023)

Bayesian update (EnKF)

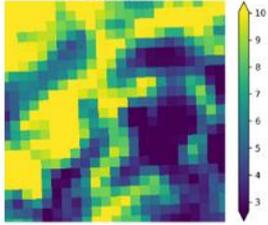


Nerini et al. (Weather Rev, 2019)



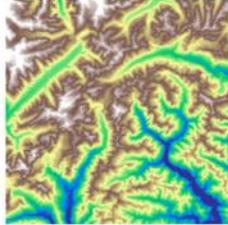
Statistical Postprocessing for seamless forecasting

Raw forecast @ 2km



+

DEM @ 50m



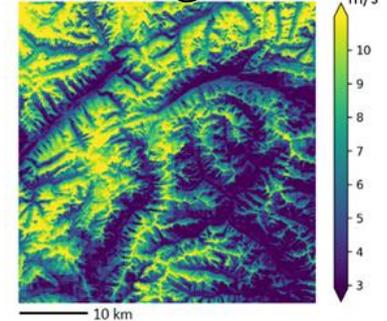
+

Station obs



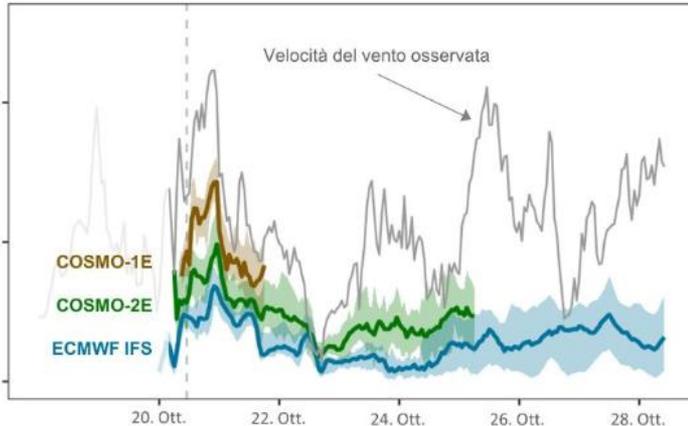
Statistical model

Wind @ 50m

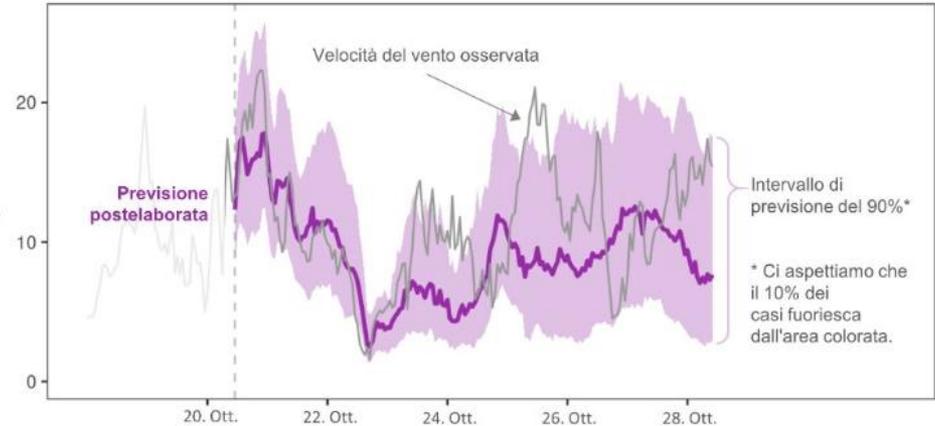


Raw forecasts

Wind speed [m/s]



Postprocessing



Postprocessing at multiple temporal scales

Problem:

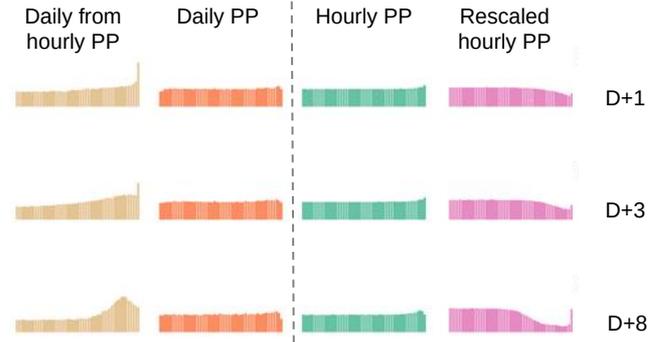
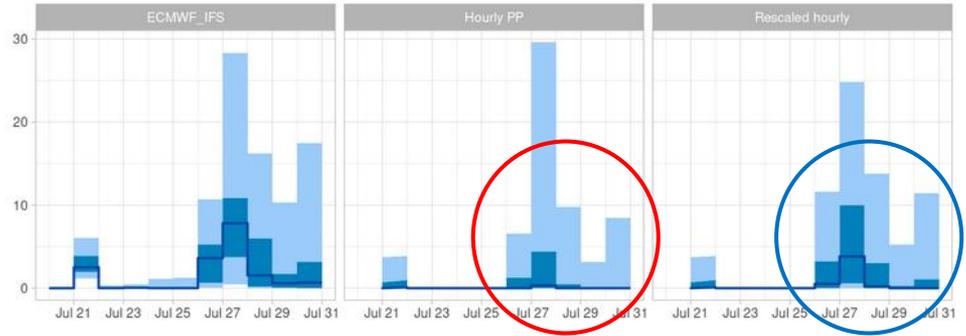
- Univariate PP on hourly precip. + limited predictability of hourly precip.
- climatological pred. (very little rain)
- **we lose rain in daily accumulations**

Solution:

Rescale hourly postprocessed precip. with daily postprocessed precip.

but remaining issues with calibration →

Forecasts of daily precipitation for Interlaken





Machine Learning

22 Jul 2024

National Weather Service (NWS) Forecasters' Perceptions of AI/ML and Its Use in Operational Forecasting

Christopher D. Wirzo,^{AB} Julie L. Demuth,^{AB} Mariana G. Cairns,^{AB} Miranda White,^{CB} Jacob Radford,^{AB} and Ann Boström^{AB}

KEYWORDS:
Social Science;
Operational forecasting;
Communications/decision making;
Artificial

ABSTRACT: Artificial intelligence and machine learning (AI/ML) have attracted a lot of attention from the atmospheric science community. The explosion of attention and development carries implications for the operational community, prompting questions about how novel AI/ML advancements will translate from research into operations. However, there is a lack of empirical evidence on how National Weather Service (NWS) forecasters, as key users, perceive AI/ML and its use in operational forecasting. This study addresses this through structured interviews conducted with 29 NWS forecasters from October 2021 to

Probabilistic machine learning

<https://doi.org/10.1038/s41586-024-08252-9>

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Published online: 04 December 2024

Open access

Check for updates

Ilan Price^{1,2,3}, Alvaro Sanchez-Gonzalez^{1,2}, Ferran Alaric^{1,2}, Andrew El-Kadi¹, Dominic Masters¹, Timo Ewalds¹, Jan Peter Battaglia^{1,2}, Remi Lam^{1,2} & Matthew Willson^{1,2}

Weather forecasts are fundamentally uncertain, and weather scenarios is crucial for important decisions. Hazardous weather to planning renewable energy have been based on numerical weather prediction (NWP) based simulations of the atmosphere. Recent data-driven weather prediction (MLWP) have produced more accurate than single NWP simulations^{1,2,3}. However, it is unclear how MLWP compares to single, deterministic forecasts that fail to represent uncertainty. Overall, MLWP has remained less accurate and re-

BAMS Article

ROBUSTNESS OF AI
C

Thomas R.

A Foundation Model for the Earth System

Cristian Bodnar^{1,2†}, Wessel D. Bruijnzeel^{1†}, Ana Lucia^{1,3†}, Mounir S. S. et al.

Geosci. Model Dev., 17, 7915–7962, 2024
<https://doi.org/10.5194/gmd-17-7915-2024>
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Geoscientific Model Development



Model evaluation paper

Do data-driven models beat numerical models in forecasting weather extremes? A comparison of IFS HRES, Pangu-Weather, and GraphCast

Leonardo Olivetti^{1,2,3} and Gabriele Messori^{1,2,4}

¹Department of Earth Sciences, Uppsala University, 75236 Uppsala, Sweden

²Swedish Centre for Impacts of Climate Extremes (climes), Uppsala University, 75236 Uppsala, Sweden

³Centre of Natural Hazards and Disaster Science (CNDS), Uppsala University, 75236 Uppsala, Sweden

⁴Department of Meteorology and Bolin Centre for Climate Research, Stockholm University, 10691 Stockholm, Sweden

Correspondence: Leonardo Olivetti (leonardo.olivetti@geo.uu.se)

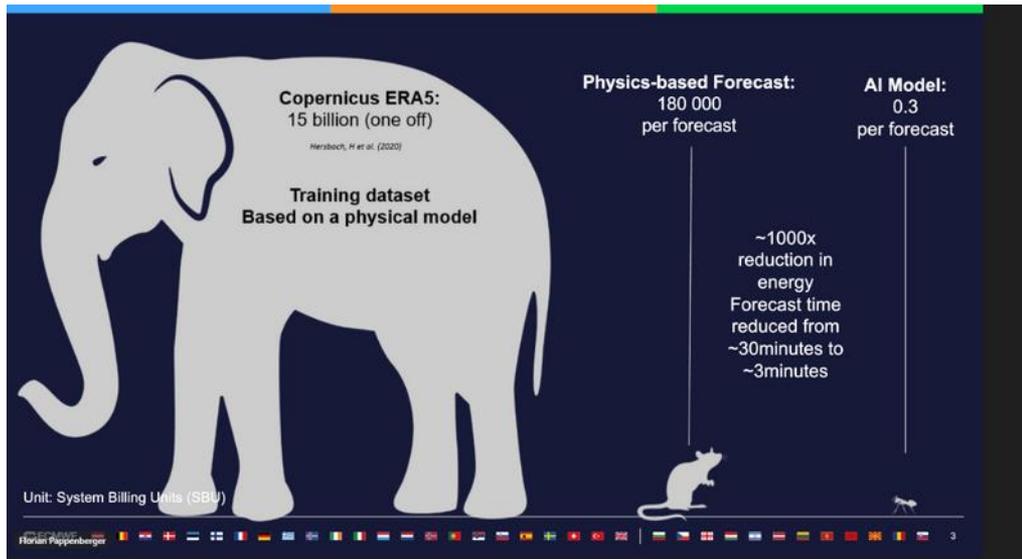
Received: 5 April 2024 – Discussion started: 10 April 2024

Revised: 16 August 2024 – Accepted: 7 September 2024 – Published: 7 November 2024

...@tudan.edu.cn;
...@163.com;
... authors contributed equally to this work.



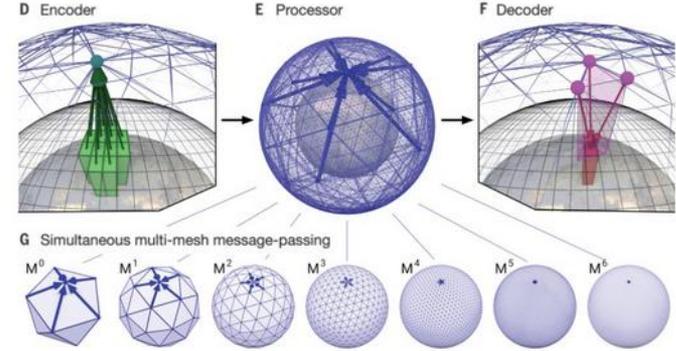
AIFS goes Operational (Feb 25, 2025)!



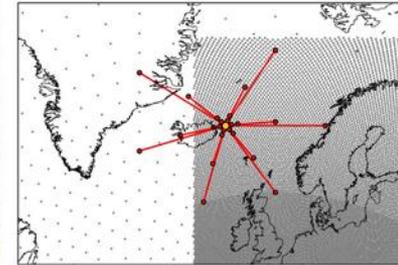
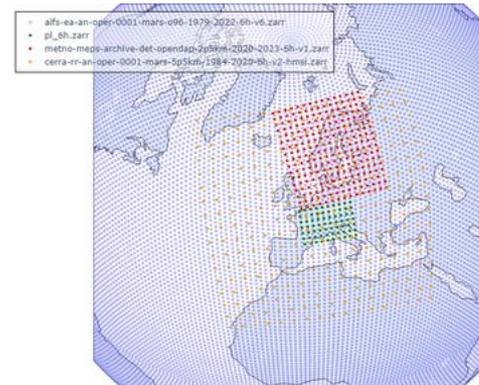


Model architecture

- **Graph-based:** use graph neural networks to encode and process input data in a flexible way.
- **Autoregressive:** rollout forecast iteratively, typically with 6h steps.
- **Stretched-grid:** high-resolution over a localised domain of interest and lower resolution elsewhere with seamless information passing across boundaries.



Remi et al. (*Nature*, 2023), "GraphCast"



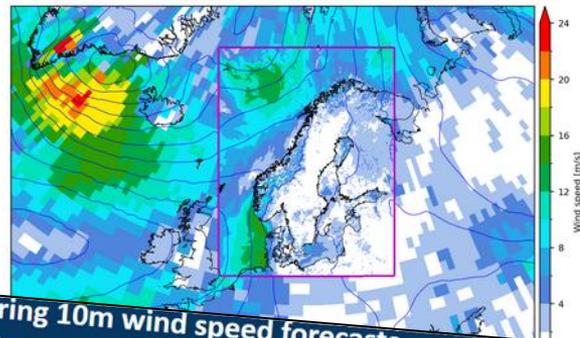
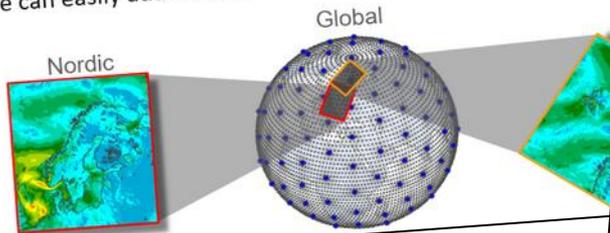


Regional Emulators

Stretched-grid approach

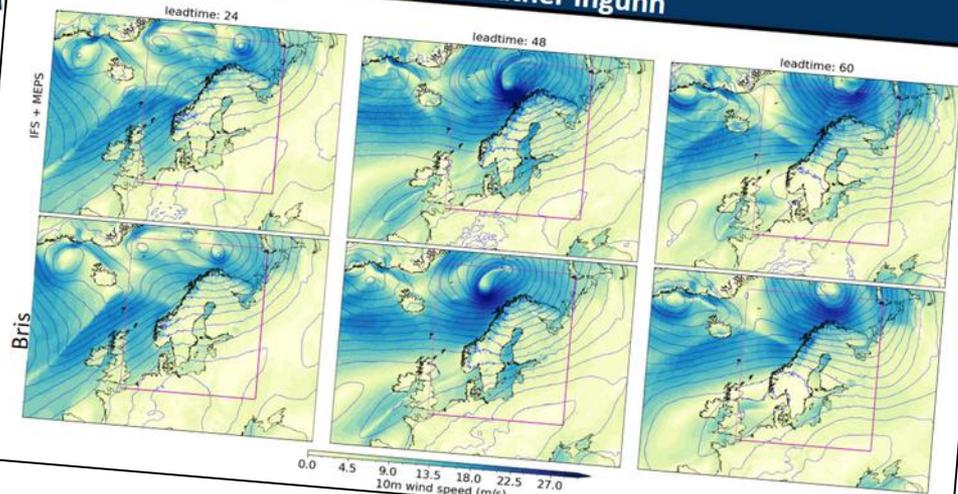
27

- Met Norway built **Bris** - a global model with high resolution over our focus areas
- Based on ECMWF AIFS/GraphCast architecture
- Developed within ECMWF's Anemoi framework
- Goal is to cover nowcasting through extended-range (21 days)
- Benefits of a stretched-grid approach
 - The model can learn from weather events all around the world
 - We can easily add further domains around the world in the fu



Comparing 10m wind speed forecasts Extreme weather Ingunn

30

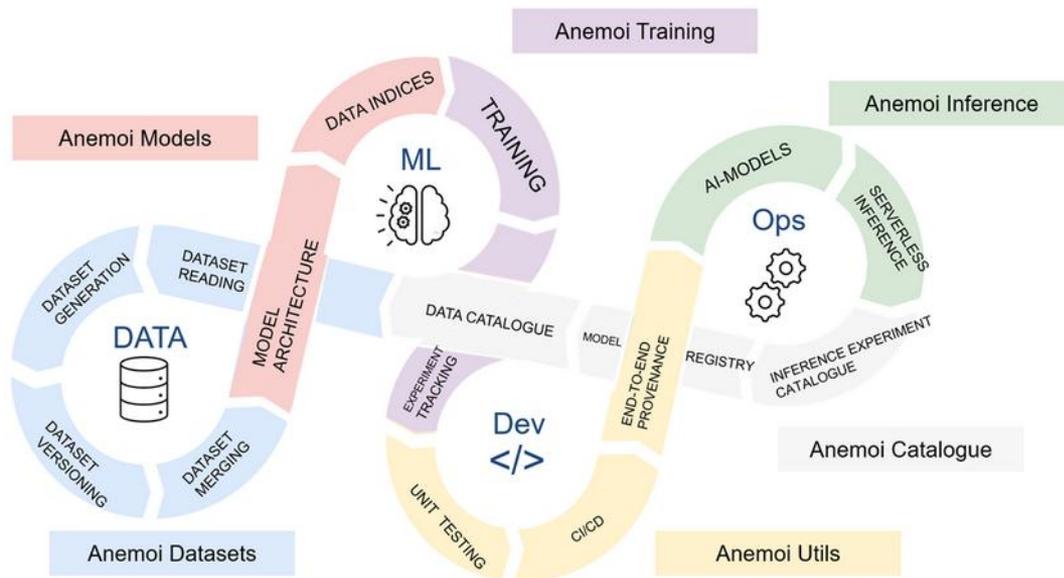




Anemoi Framework



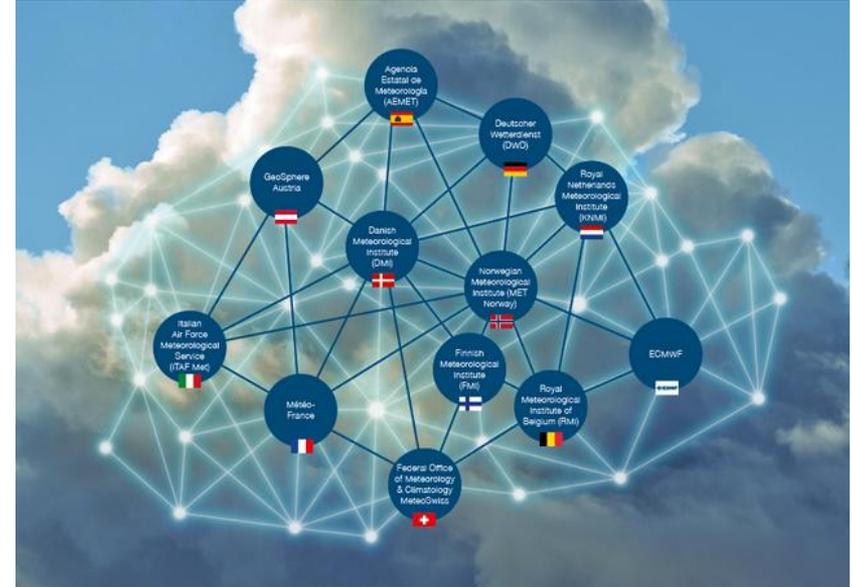
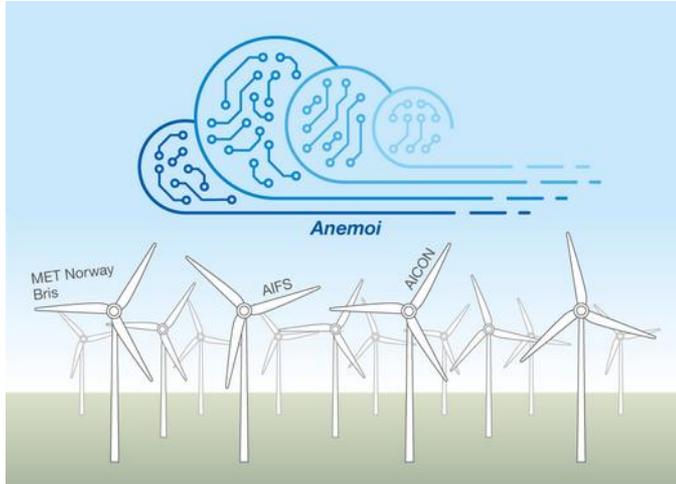
- Provide cutting-edge ML tools for meteorological applications covering the whole ML lifecycle.
- Foster a collaborative and open-source ecosystem.
- Facilitate R2O, reduce maintenance.





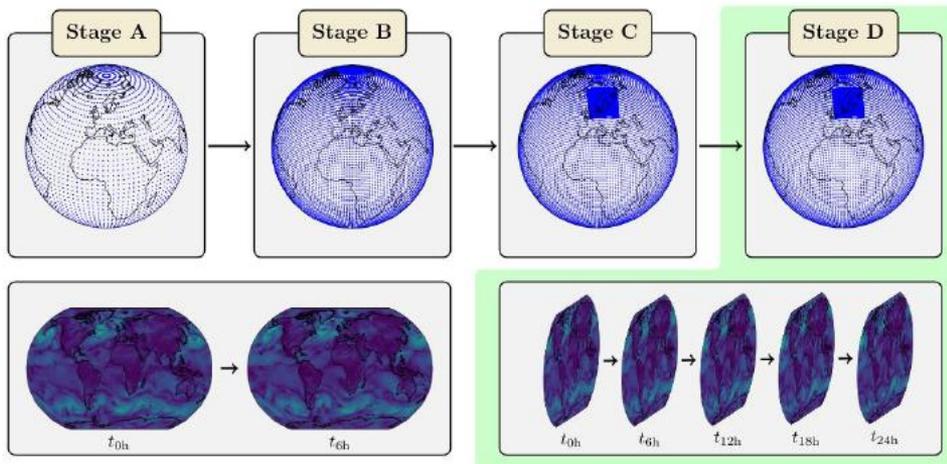
Anemoi Community

- Collective expertise of 12 European meteorological institutions, led by ECMWF.
- Over 40 contributors, 700 pull requests and counting.





Data-driven regional forecasting



Stage	A: 1° global	B: 0.25° global	C: 0.25° + 2.5km	D: rollout
Iterations	200,000	15,000	5,000	300
GPU hours	1,750	2,500	1,900	180

ECMWF to provide pre-trained Stage B models!

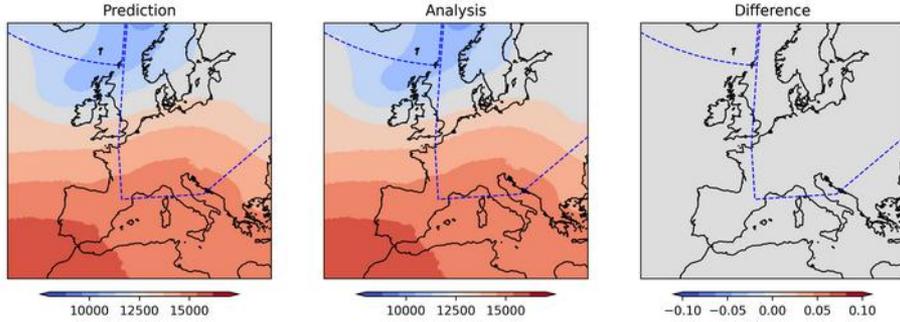
Transfer Learning:

- Sequentially adapt the model to more complex tasks.
- Harness the greater data availability of ERA5.
- Gradually refines the model, allowing it to reach a local minima.
- Drastic increase in performance vs starting directly at stage C.

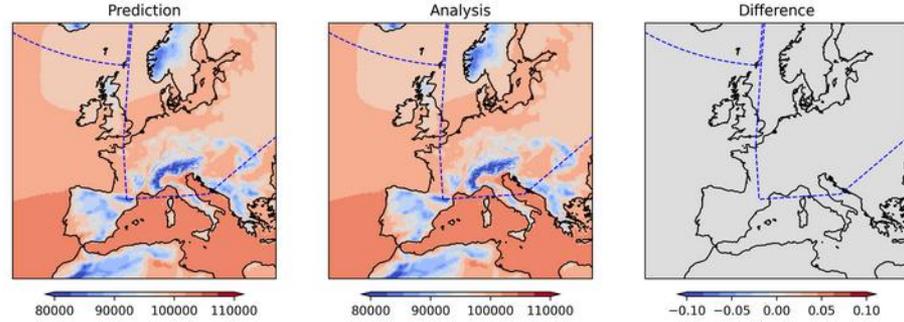


AICON Results

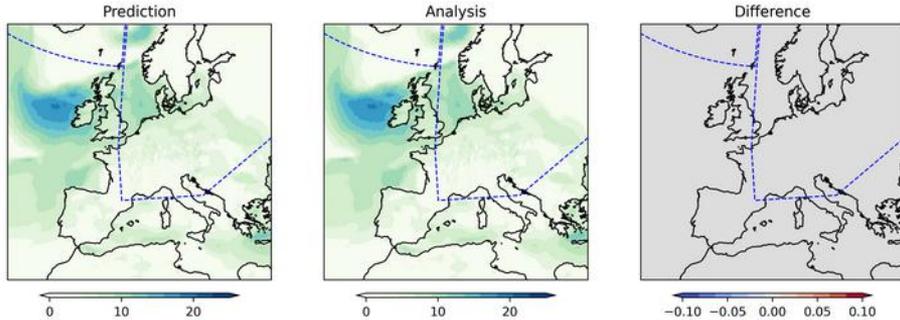
z_850 2020-02-01 00:00 (+0h)



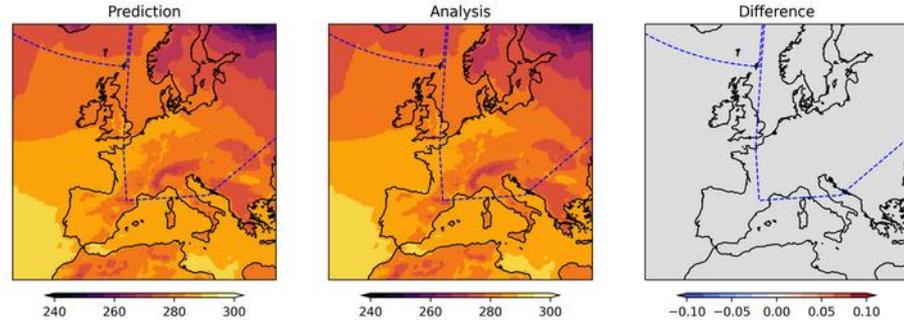
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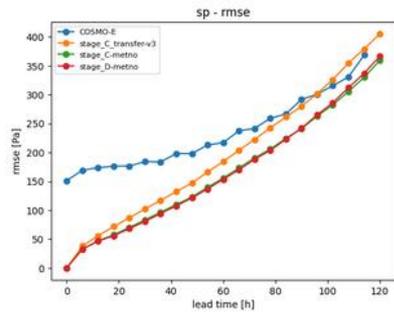
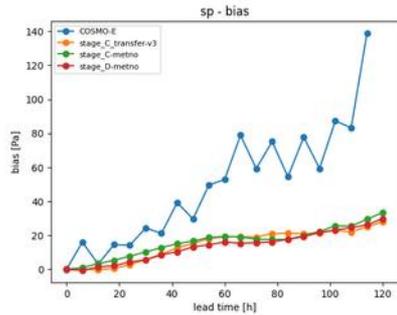
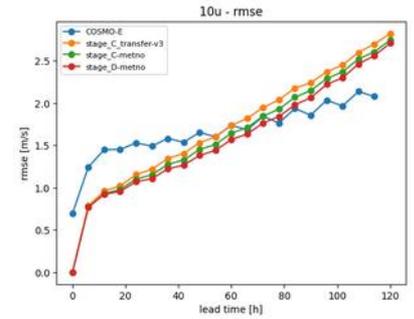
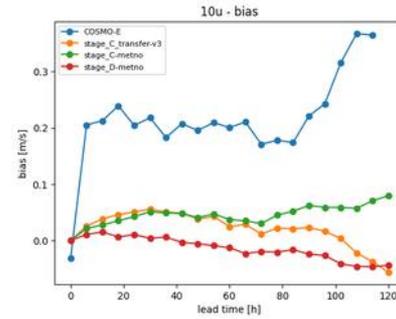
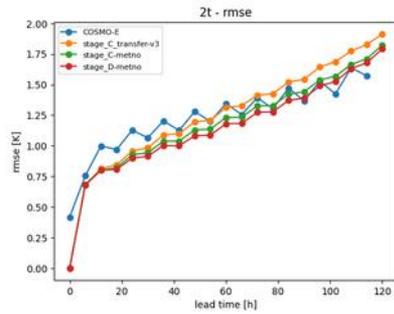
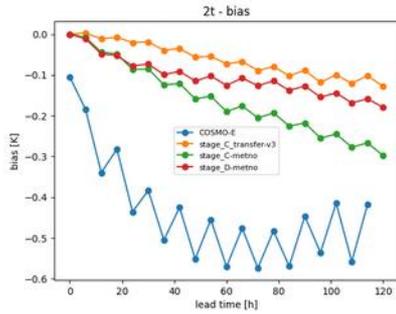


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AICON „Verification“





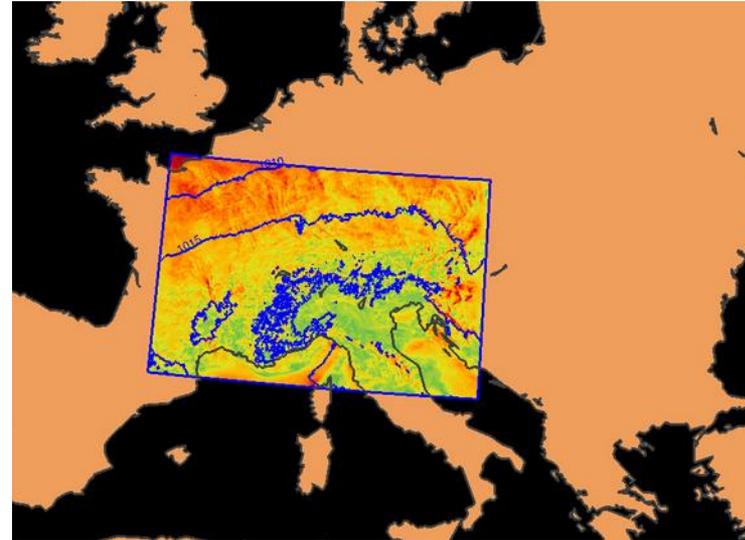
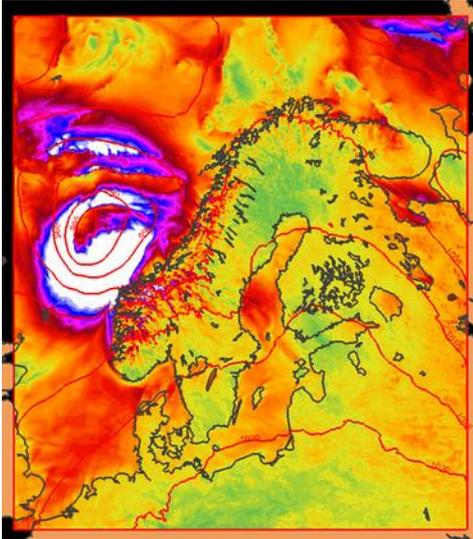
Running Bris in Switzerland

Trained on:

- MEPS 2.5km analyses 2020-2023
- 1000 * 950 grid points
- Biggest mountain: 2019 m

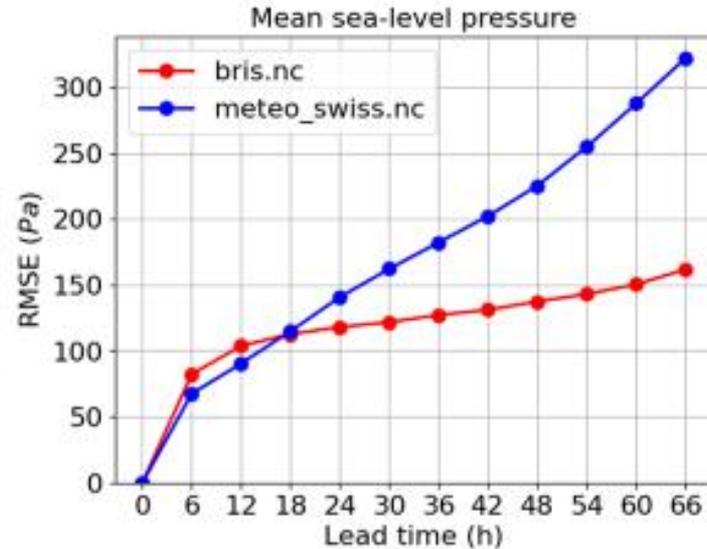
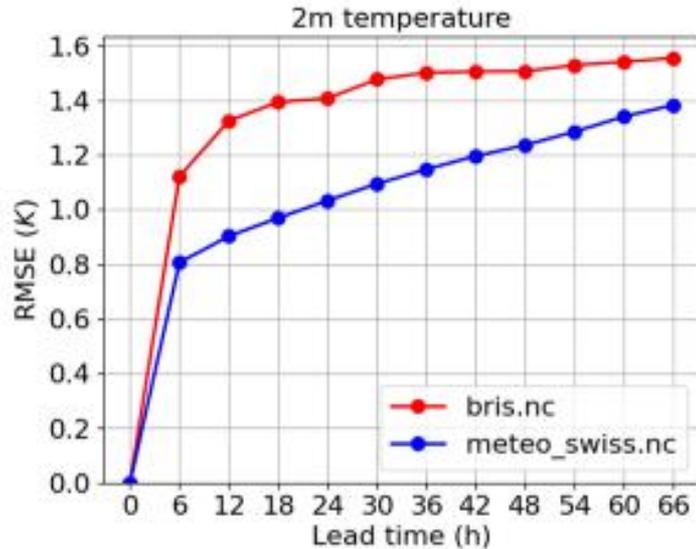
Inference on:

- COSMO 2.2km analyses
- 290 * 582 gridpoints
- Biggest mountain: 3867 m



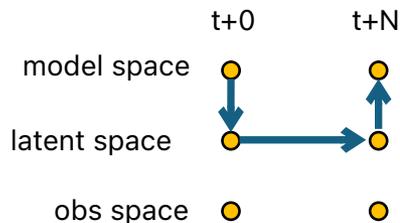
How robust are stretched-grid models?

Running Bris on the Swiss domain



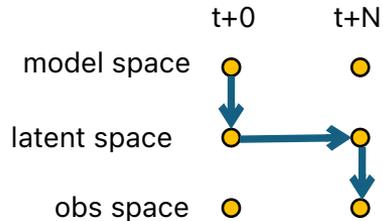
1) Predict analysis from analysis

e.g. current AIFS



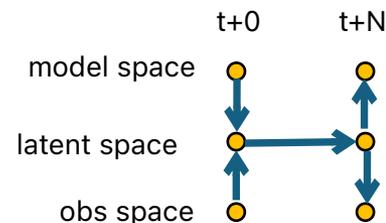
2) Predict obs targets from analysis ICs

e.g. fine tune AIFS to predict SYNOPs



3) Augment analysis driven ML with observations

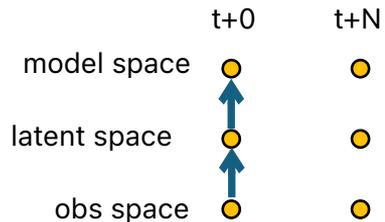
e.g. obs not used by 4D-Var



Augmenting existing analysis driven approaches with observational data

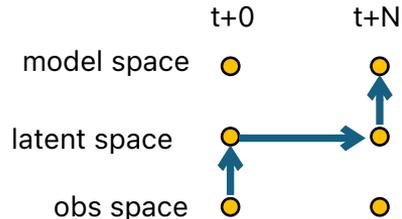
4) Learn the analysis

e.g. emulate 4D-Var



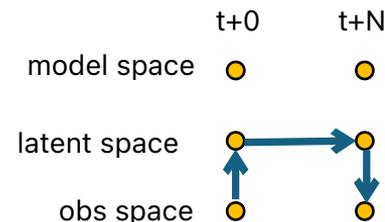
5) Predict future analysis from obs

e.g. make predictions in model space
use reanalysis as truth



6) Predict future obs from obs

e.g. make predictions in obs space,
using obs as truth



Initializing + learning from
observations



EUR

Direct Observation Prediction – making a forecast directly from observations



Data Assimilation – Multiple Encoders/Decoders

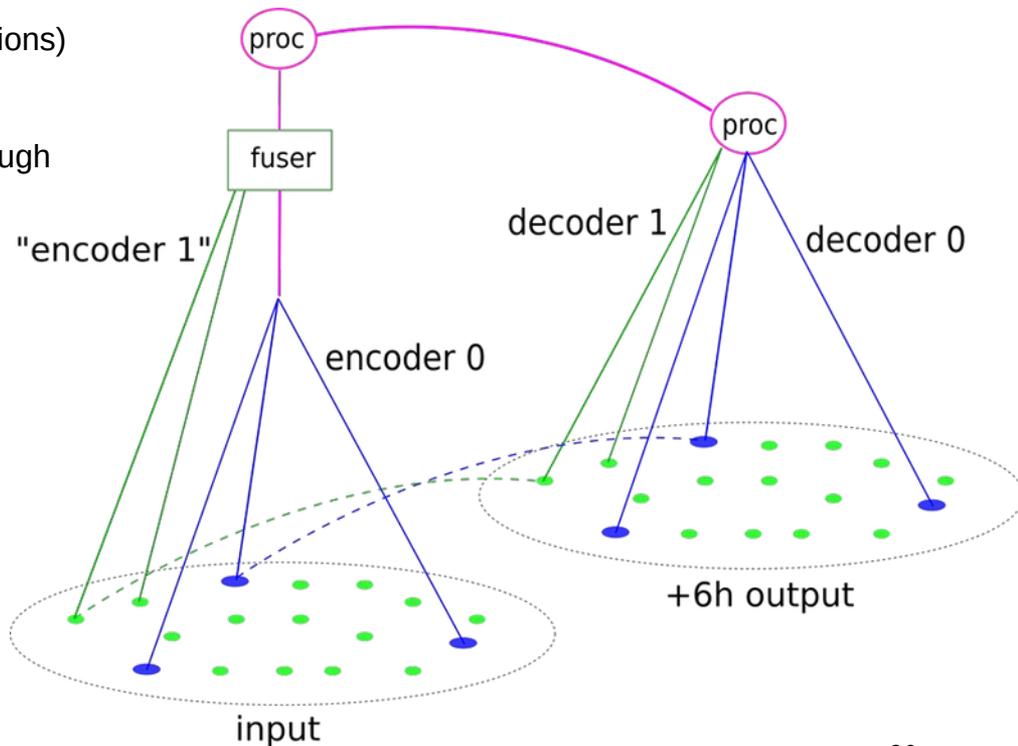
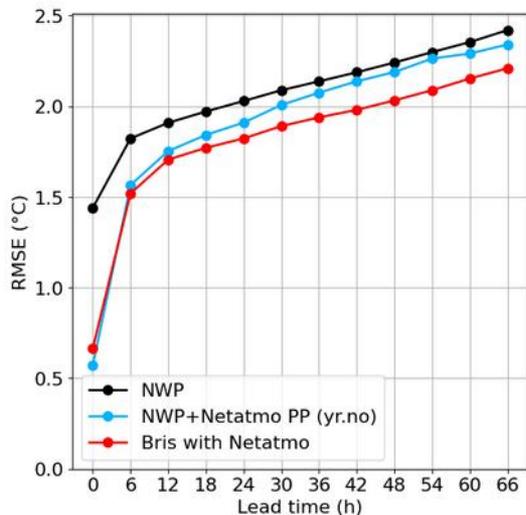
Blue points is the standard analysis input

Green points secondary data source (e.g. observations)

Multiple encoders in sequence

- Encoder 0 encodes the analysis input
- Encoder 1 encodes the secondary input through a fuser (perceiver)

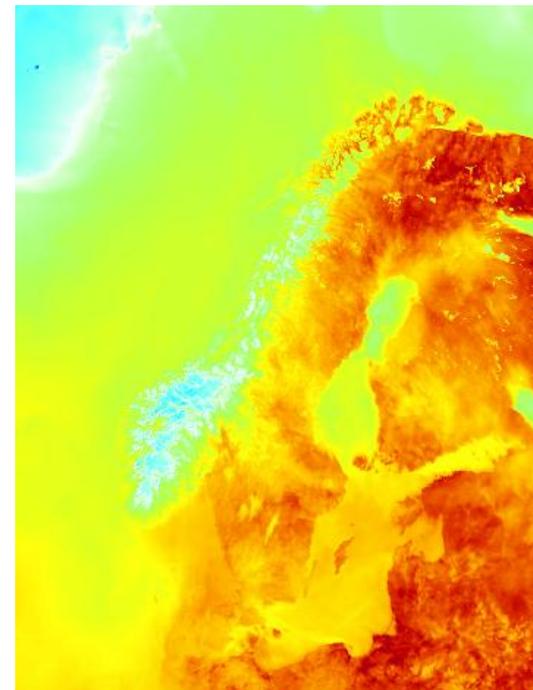
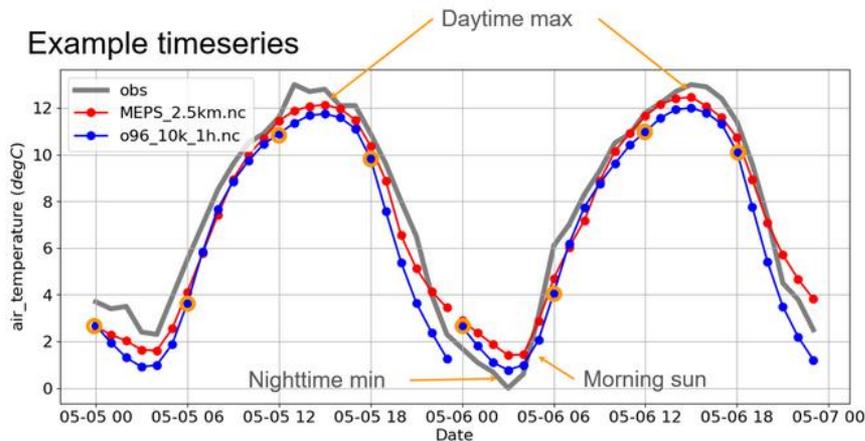
Multiple decoders (similar to single decoder case)





Time Interpolator

- Training a model directly at 1h steps would decrease model skill during long rollouts.
- Time interpolation allows to progressively produce finer temporal resolution forecasts while maintaining model skill at long lead times.



Hourly 2m Temperature

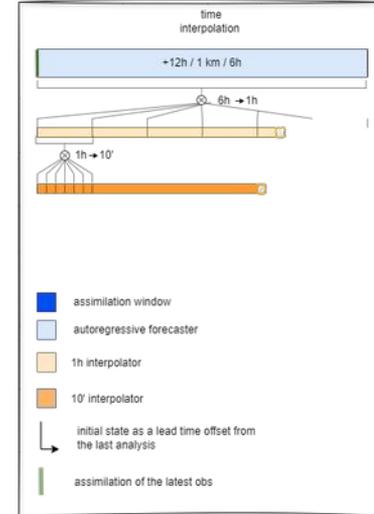
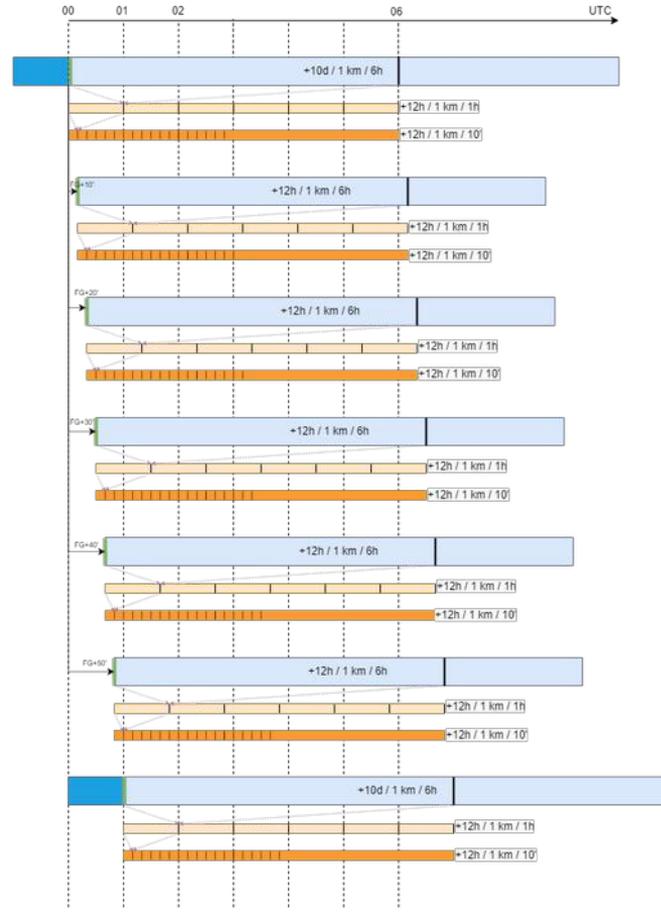


Putting it together: Seamless RUC

Components

- ❑ Conventional DA (KENDA)
- ❑ Forecaster (6 hourly outputs)
- ❑ Time interpolator (hourly outputs)
- ❑ Data assimilator

Seamless by design.





Wrap up

- Conventional approach is “post-hoc” seamless
 - Blend of forecasts that historically have been developed in separated communities.
- ML is changing the traditional boundaries of how things are being done
 - DA, nowcasting, postprocessing, downscaling – all in a single model!
- New community are forming around ML, offering synergies and enabling quicker adoption.
 - Anemoi: sharing data and sharing models!
- MeteoSwiss is building an ML-based model that can be competitive in quality for nowcasting-, short, and medium-range forecasts (“Seamless RUC”).



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Federal Department of Home Affairs FDHA
Federal Office of Meteorology and Climatology **MeteoSwiss**

MeteoSwiss

Operation Center 1
CH-8058 Zurich-Airport
T +41 58 460 91 11
www.meteoswiss.ch

More questions? Get in touch! [Daniele .Nerini@meteoswiss.ch](mailto:Daniele.Nerini@meteoswiss.ch)

MeteoSvizzera

Via ai Monti 146
CH-6605 Locarno-Monti
T +41 58 460 92 22
www.meteosvizzera.ch

MétéoSuisse

7bis, av. de la Paix
CH-1211 Genève 2
T +41 58 460 98 88
www.meteosuisse.ch

MétéoSuisse

Chemin de l'Aérologie
CH-1530 Payerne
T +41 58 460 94 44
www.meteosuisse.ch

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