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# How ML is transforming our approach to seamless weather forecasting

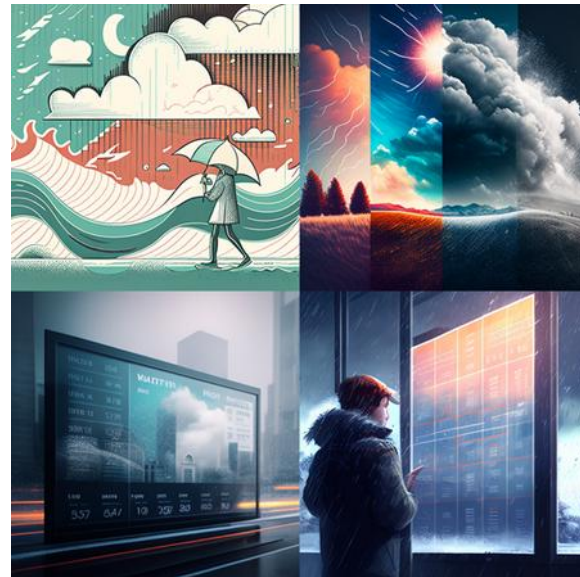
PrePEP Conference, Seamless Prediction  
Bonn, 19.03.2025

Daniele Nerini

with contributions from

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

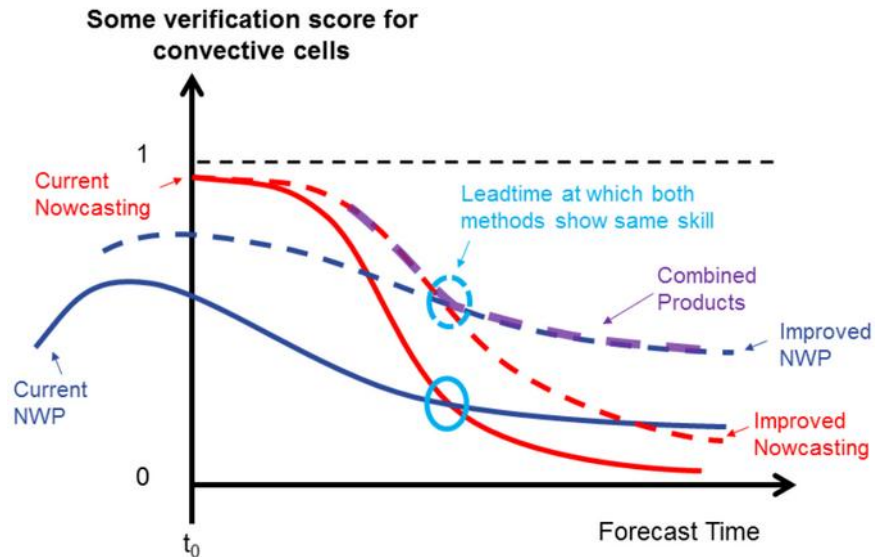
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# How to Seamless

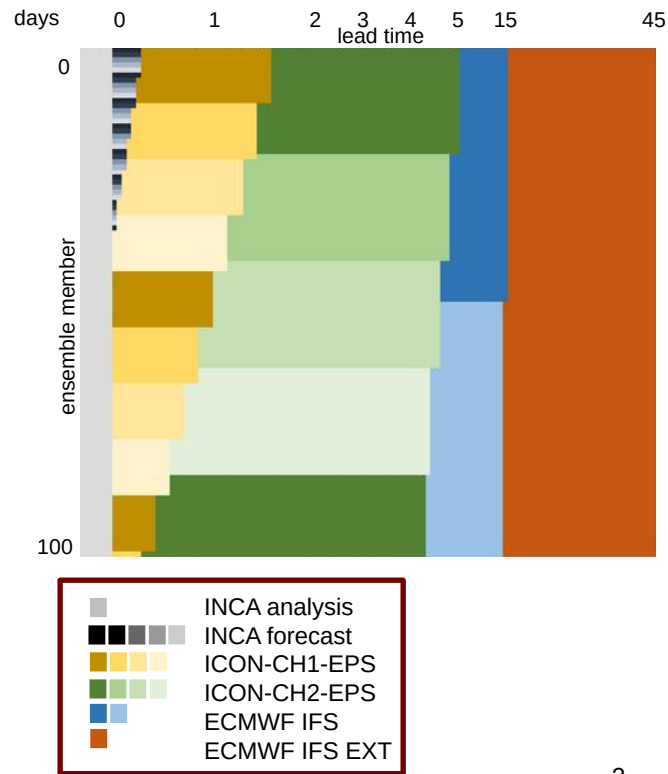
## Basic concept of SINFONY



Source:

[https://www.dwd.de/DE/forschung/forschungsprogramme/sinfony\\_iafe/sinfony\\_node.html](https://www.dwd.de/DE/forschung/forschungsprogramme/sinfony_iafe/sinfony_node.html)

## “Full-stack” seamless forecast



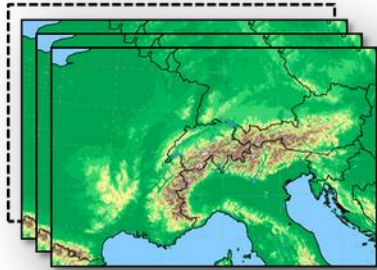


# Improving NWP

## ICON-CH1-EPS und ICON-CH2-EPS

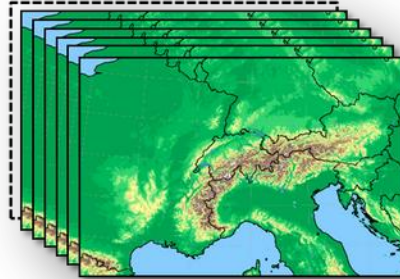
### ICON-CH1-EPS

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

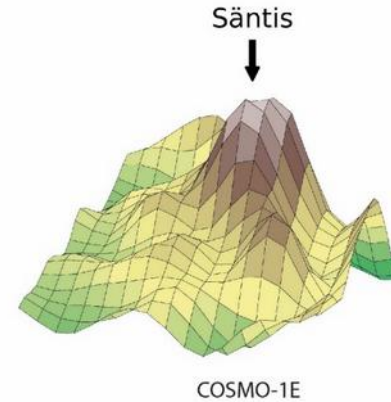


### ICON-CH2-EPS

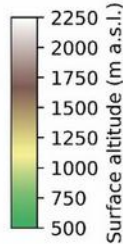
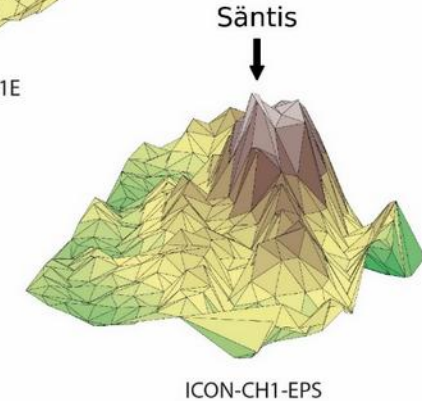
5 day forecasts, 4x per day  
2.2 km grid size  
21 ensemble members



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



Same grid resolution, but  
more accurate topography



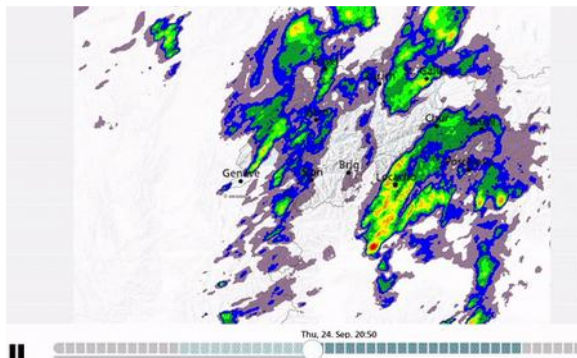


# Improving nowcasting

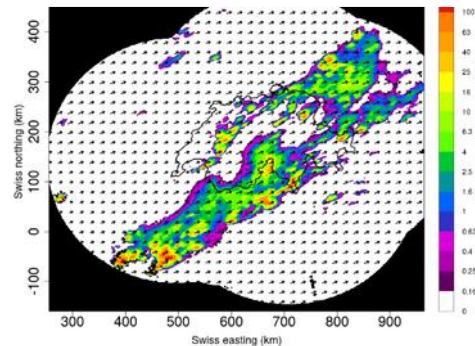
- Nowprecip is MeteoSwiss' operational precipitation nowcasting system.
- 10min / 1km res, +6 hrs
- Nowprecip =

radar extrapolation  
+ stochastic perturbations  
+ tendency from NWP

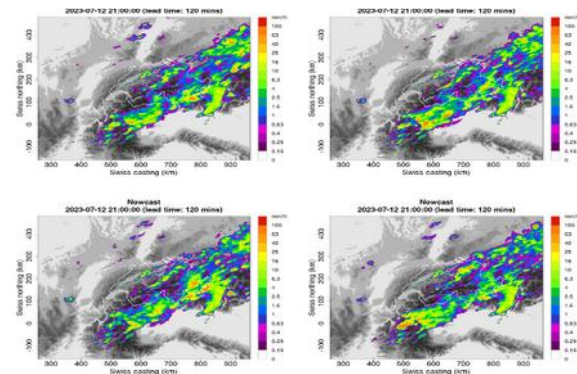
## Realistic and seamless



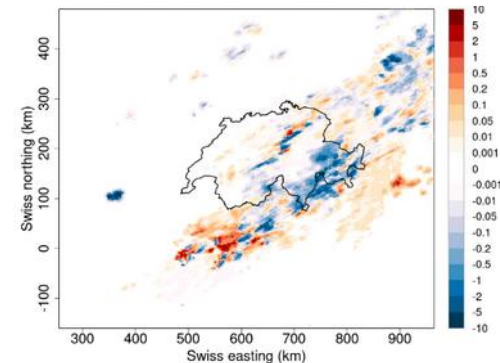
## Optical flow



## Ensemble



## Growth-decay maps

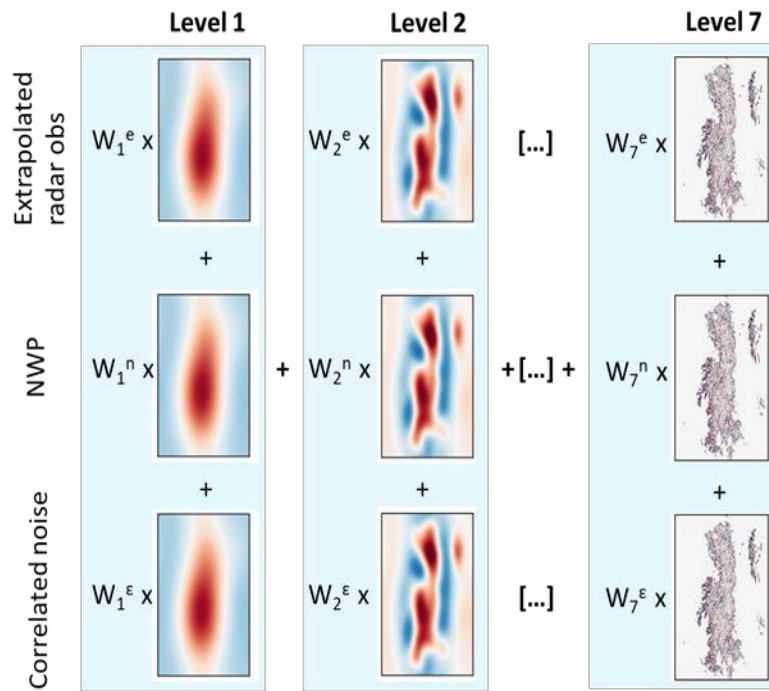






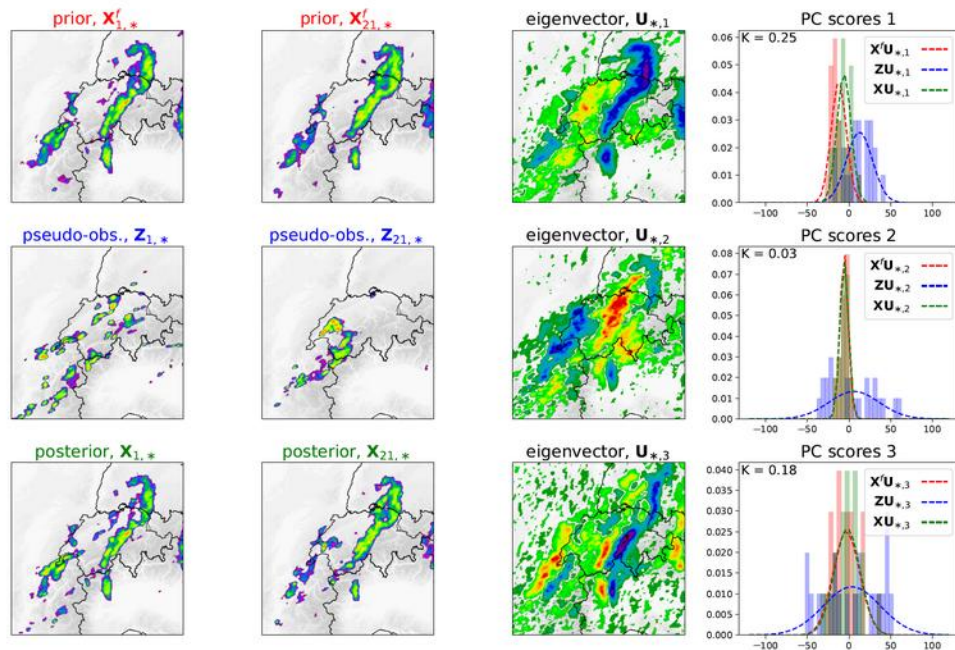
# Improving blending

## Scale dependent (STEPS)



Imhoff et al. (QJRM, 2023)

## Bayesian update (EnKF)

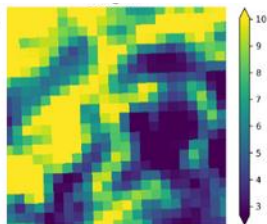


Nerini et al. (Weather Rev, 2019)



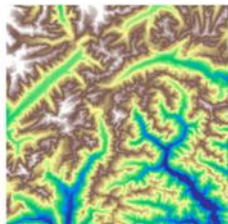
# Statistical Postprocessing for seamless forecasting

Raw forecast @ 2km



+

DEM @ 50m



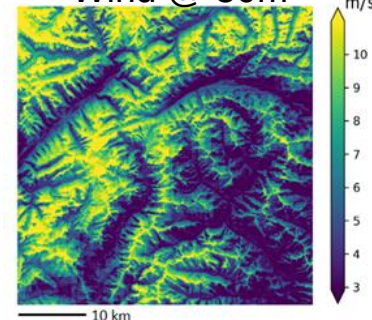
+

Station obs



Statistical  
model

Wind @ 50m

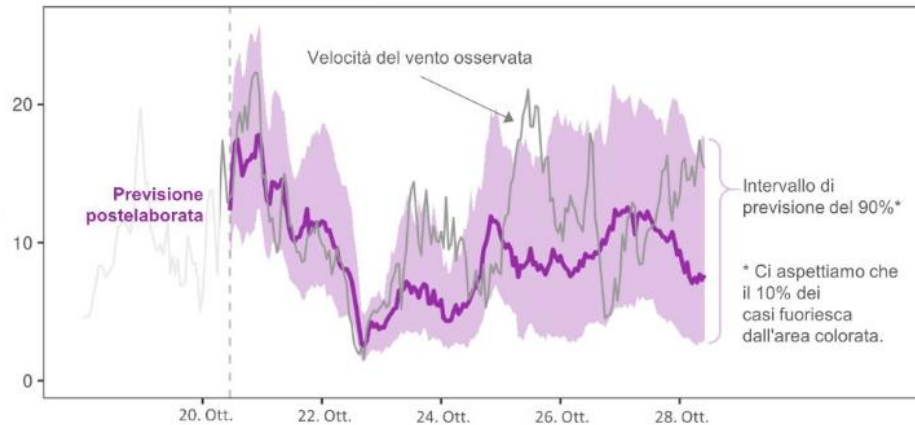


Raw forecasts

Wind speed [m/s]



Postprocessing





# Postprocessing at multiple temporal scales

Problem:

Univariate PP on hourly precip. +  
limited predictability of hourly precip.

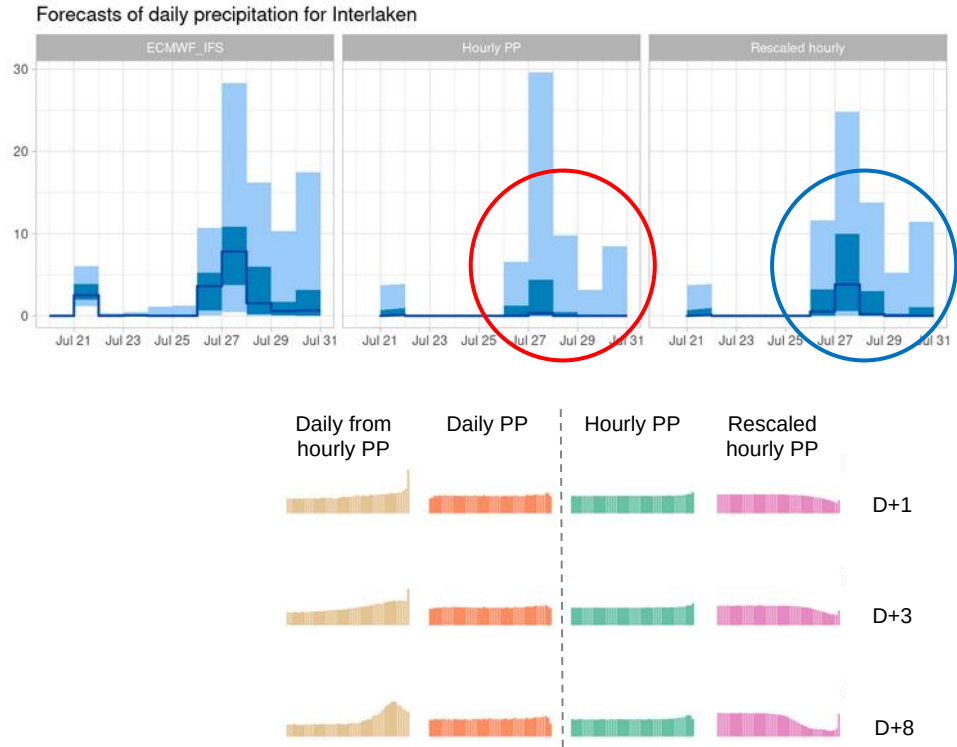
→ climatological pred. (very little rain)

→ **we lose rain in daily accumulations**

Solution:

**Rescale hourly postprocessed precip.  
with daily postprocessed precip.**

but remaining issues with calibration →





# Machine Learning

22 Jul 2024

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

Christopher D. Wirz<sup>a,b</sup>, Julie L. Demuth<sup>a,b</sup>, Mariana G. Cairns<sup>a,b</sup>,  
Miranda White<sup>c,d</sup>, Jacob Radford<sup>a,d,e</sup> and Ann Boström<sup>a,f</sup>

**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>

Received: 30 April 2024

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Open access

Check for updates

Ilan Price<sup>1,2,3,4</sup>, Alvaro Sanchez-Gonzalez<sup>1,2,3</sup>, Ferran Alcaraz<sup>1,2,3</sup>, Andrew El-Kadi<sup>1</sup>, Dominic Masters<sup>1</sup>, Timo Ewalds<sup>1</sup>, Peter Battaglia<sup>1,2,3</sup>, Remi Lam<sup>1,2,3</sup> & Matthew Willson<sup>1,2,3</sup>

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) simulations of the atmosphere. Recent data-based simulations of the atmosphere (MLWP) have produced error than single NWP simulations<sup>1,2,3</sup>. However, on single, deterministic forecasts that fail to represent overall, MLWP has remained less accurate and re-

**BAMS**  
Article

ROBUSTNESS OF AI  
C

Thomas Rieck

## A Foundation Model for the Earth System

Cristian Bodnar<sup>1,2†</sup>, Wessel D. Bruijnzeel<sup>1†</sup>, Ana Lucia<sup>1,3†</sup>, Maria S. S. L. L.

Geosci. Model Dev., 17, 7915–7962, 2024  
<https://doi.org/10.5194/gmd-17-7915-2024>  
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## Do data-driven models beat numerical models in forecasting weather extremes? A comparison of IFS HRES, Pangu-Weather, and GraphCast

Leonardo Olivetti<sup>1,2,3</sup> and Gabriele Messori<sup>1,2,4</sup>

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

<sup>4</sup>Department of Meteorology and Bolin Centre for Climate Research, Stockholm University, 10691 Stockholm, Sweden

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

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

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Model evaluation paper



Geoscientific  
Model Development

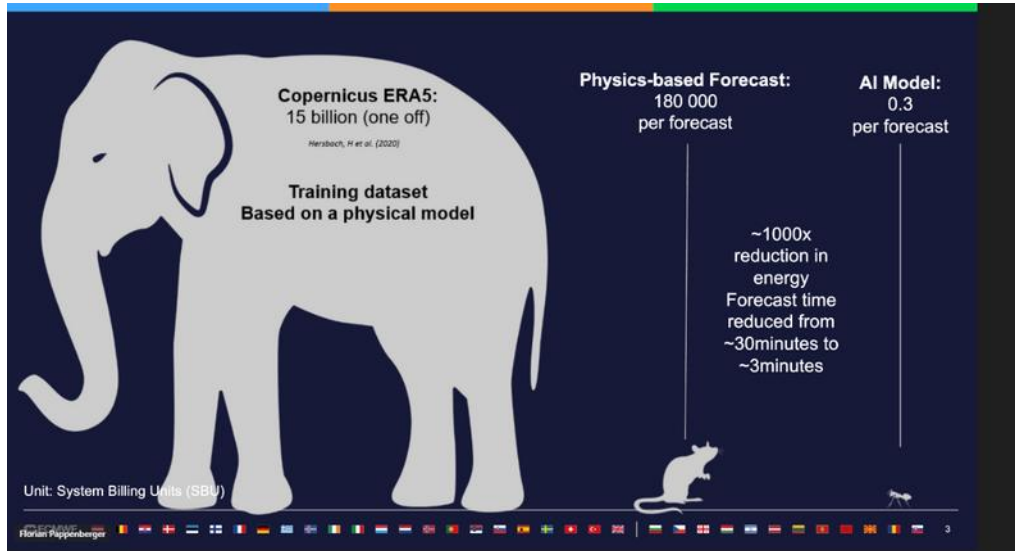
Open Access





# AIFS goes Operational (Feb 25, 2025)!

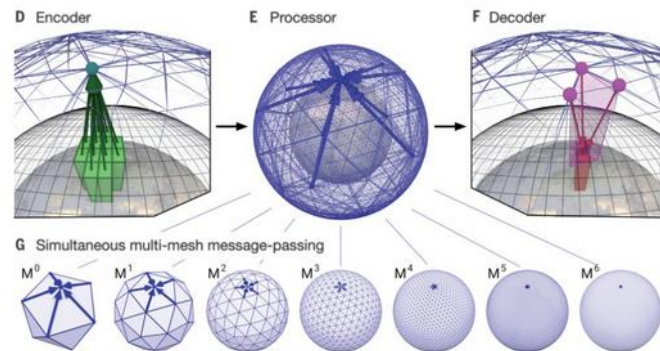
**AIFS** OPERATIONAL



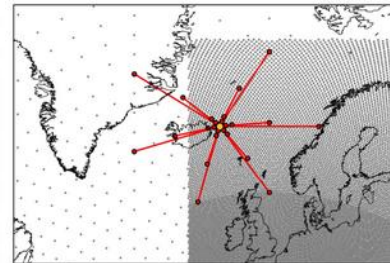
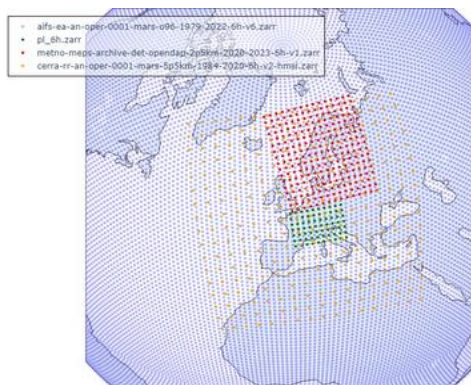


# Model architecture

- **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"

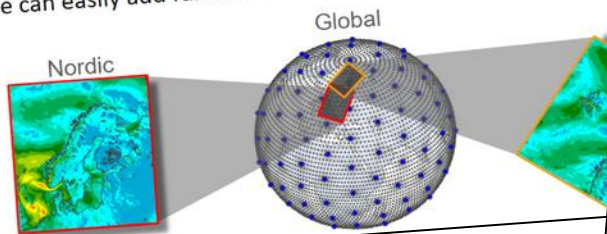




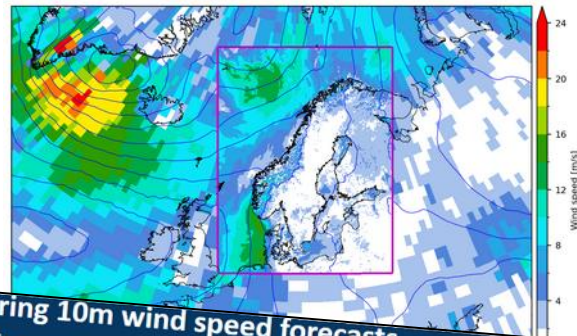
# Regional Emulators

## Stretched-grid approach

- 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 future

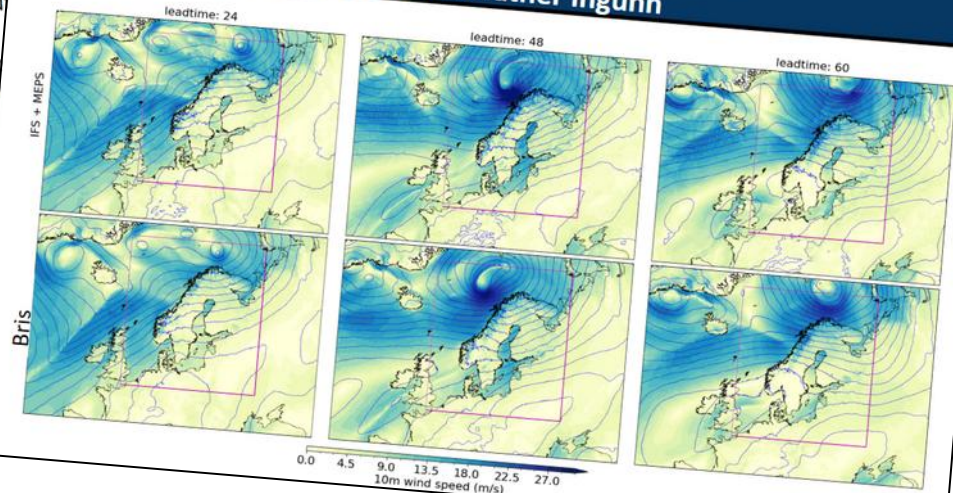


27



## Comparing 10m wind speed forecasts Extreme weather Ingunn

30



11

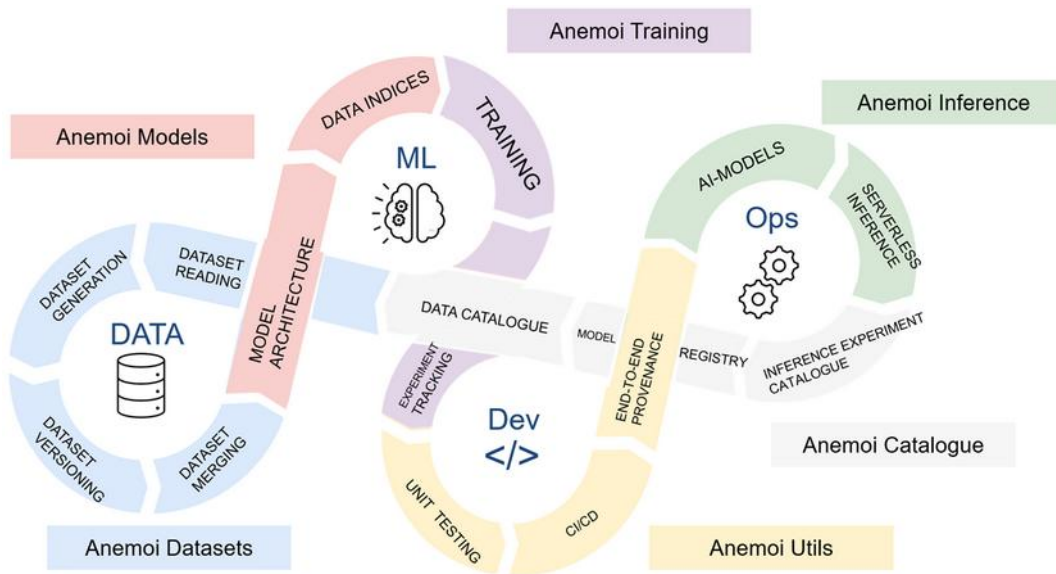




# Anemoi Framework



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

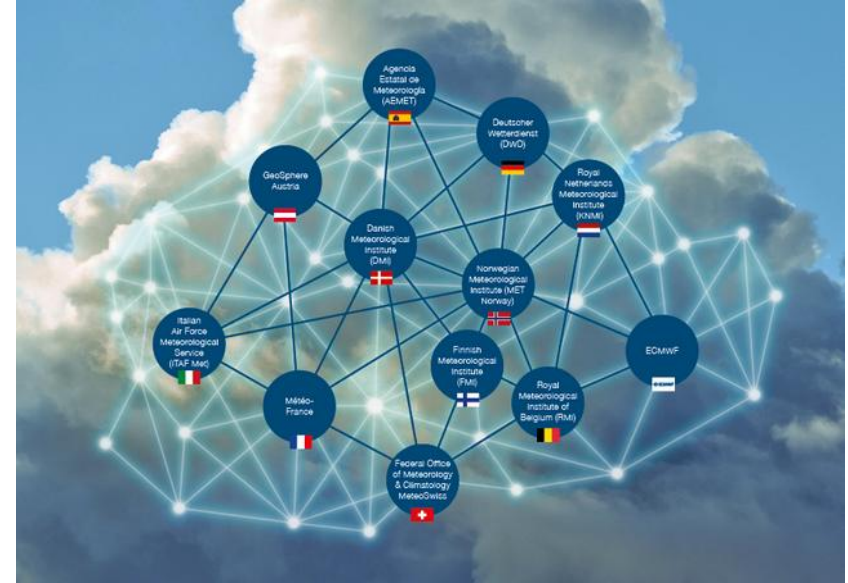
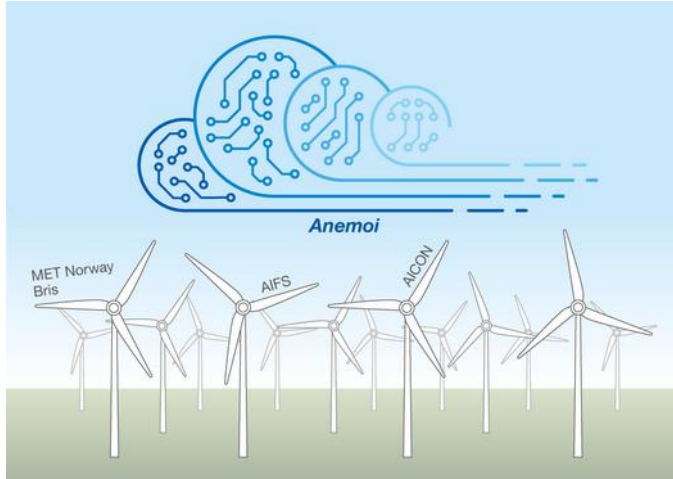






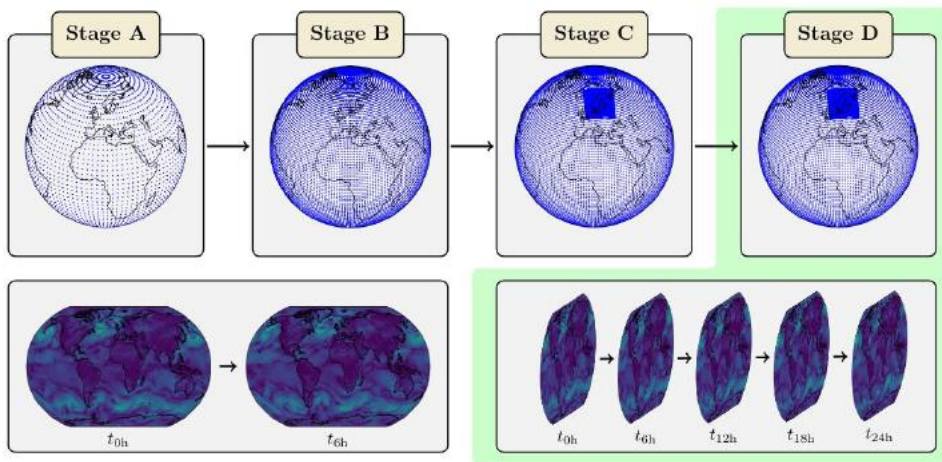
# Anemoi Community

- 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!

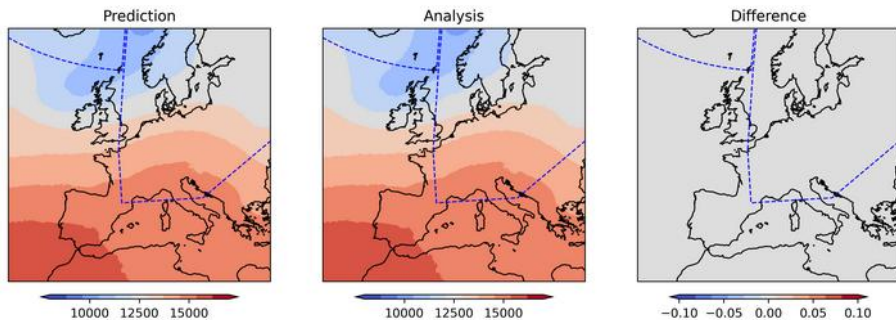
## Transfer Learning:

- 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.

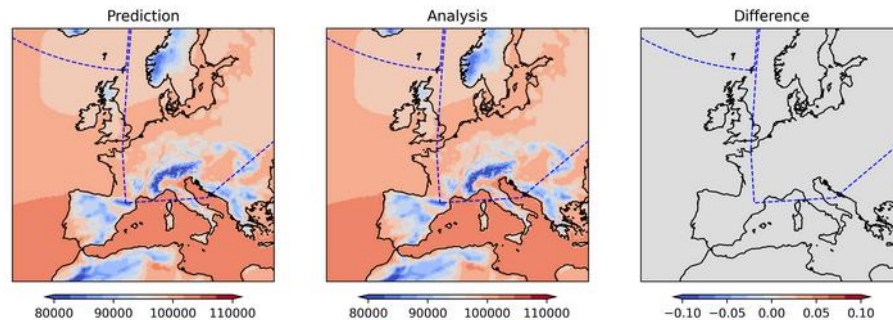


# AICON Results

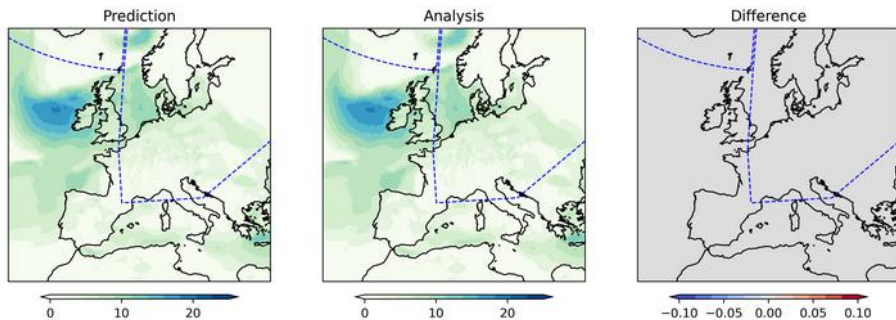
z\_850 2020-02-01 00:00 (+0h)



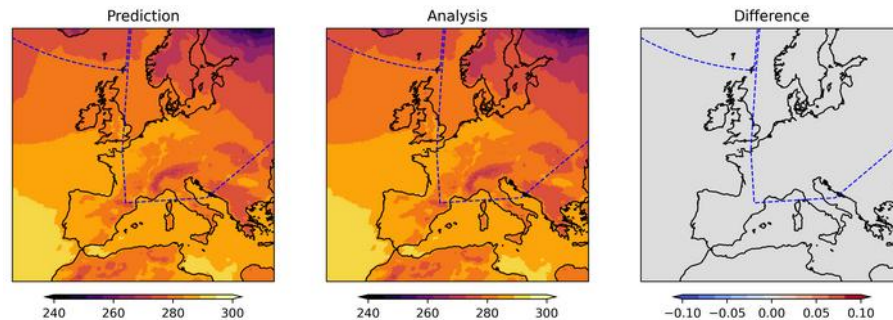
sp 2020-02-01 00:00 (+0h)



10u 2020-02-01 00:00 (+0h)

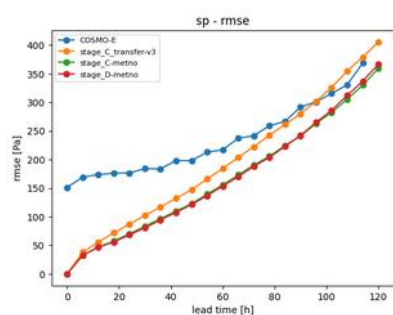
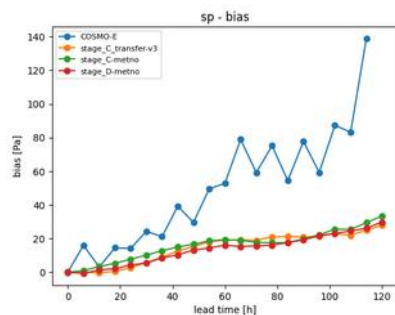
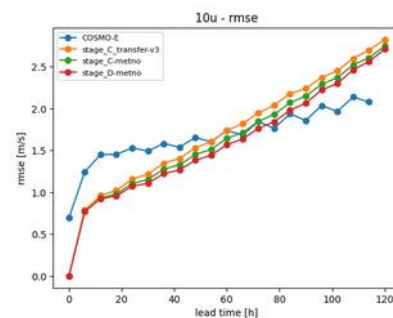
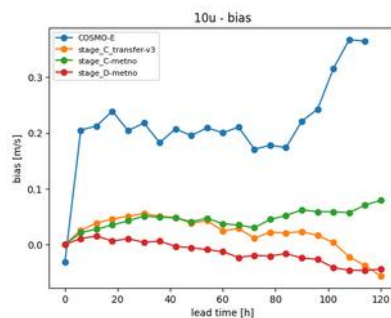
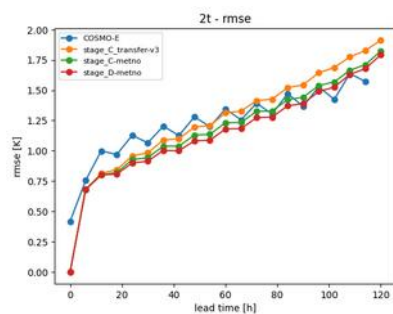
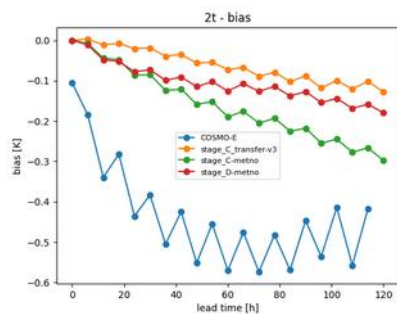


2t 2020-02-01 00:00 (+0h)





# AICON „Verification“







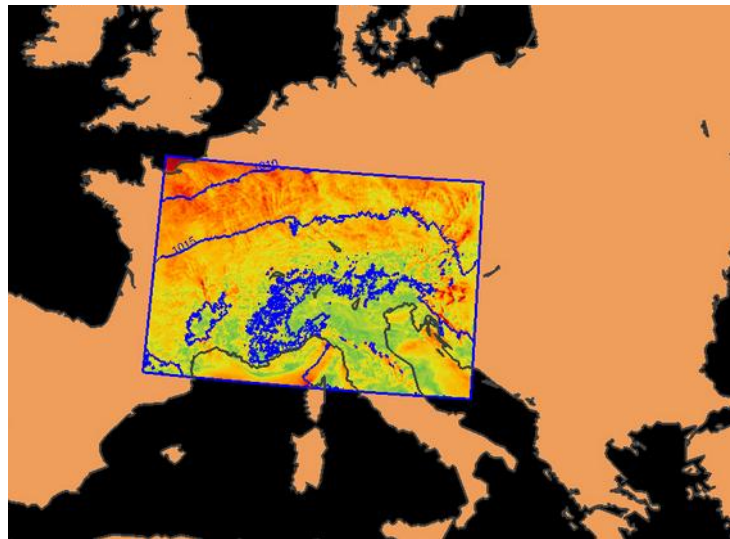
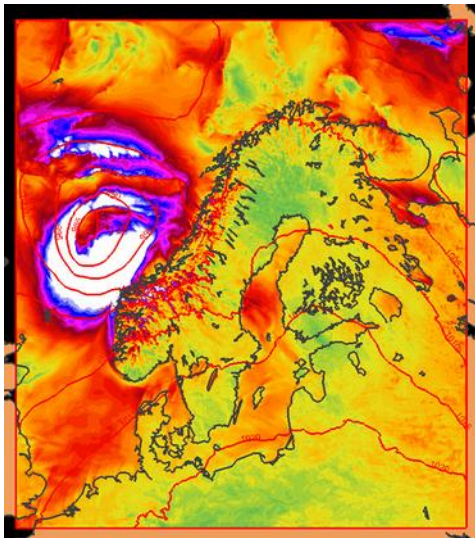
# Running Bris in Switzerland

Trained on:

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

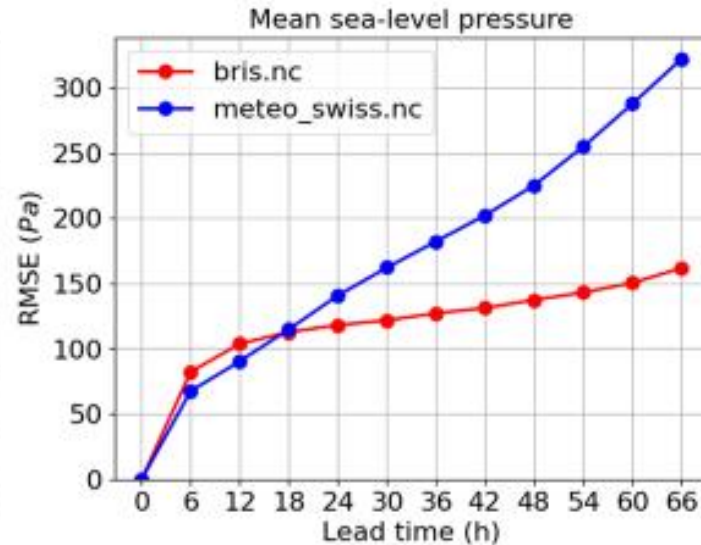
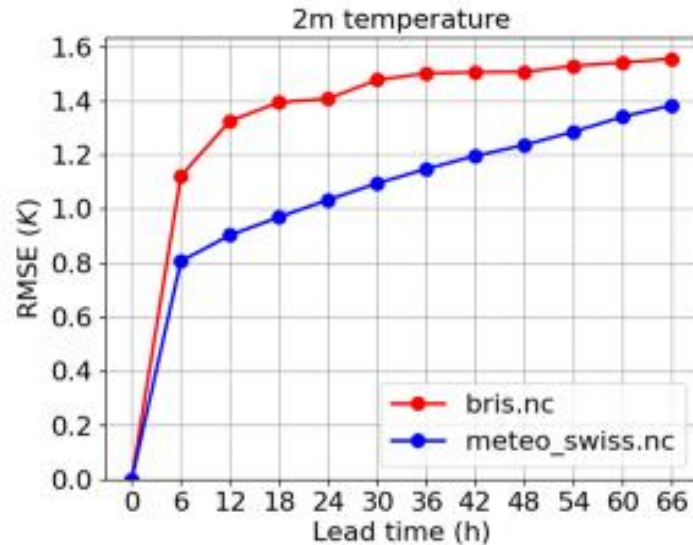
Inference on:

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



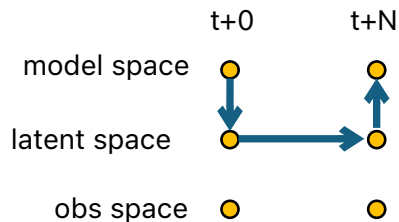
# How robust are stretched-grid models?

## Running Bris on the Swiss domain



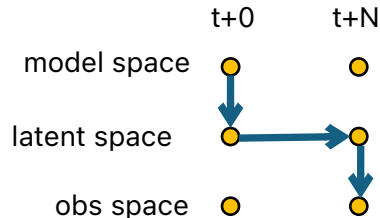
## 1) Predict analysis from analysis

e.g. current AIFS



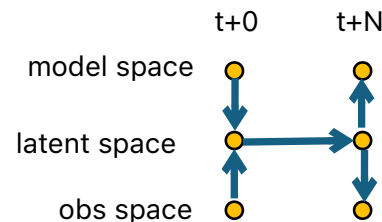
## 2) Predict obs targets from analysis ICs

e.g. fine tune AIFS to predict SYNOPs



## 3) Augment analysis driven ML with obs

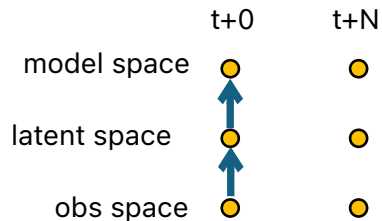
e.g. obs not used by 4D-Var



Augmenting existing analysis driven approaches with observational data

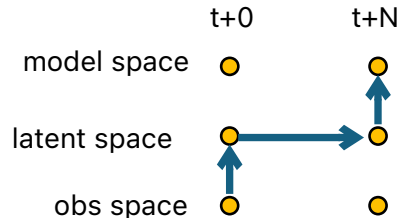
## 4) Learn the analysis

e.g. emulate 4D-Var



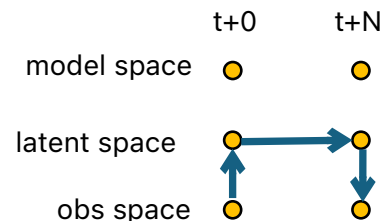
## 5) Predict future analysis from obs

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

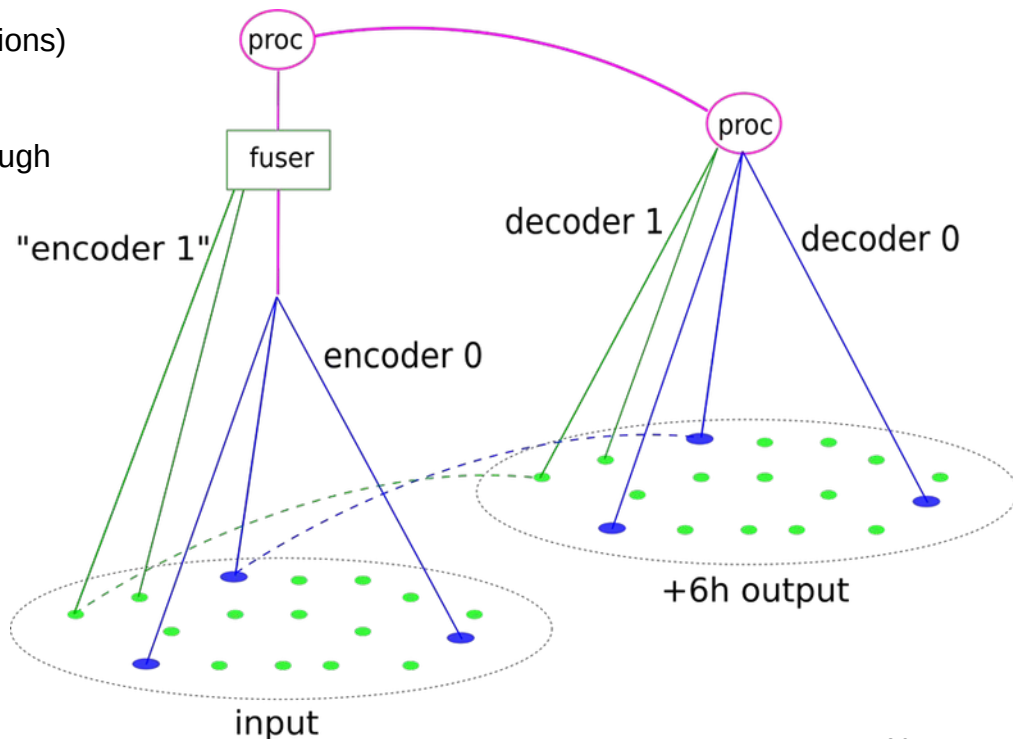
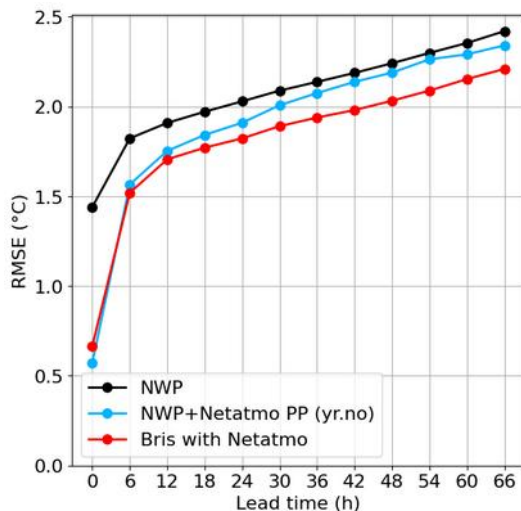
Blue points is the standard analysis input

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)

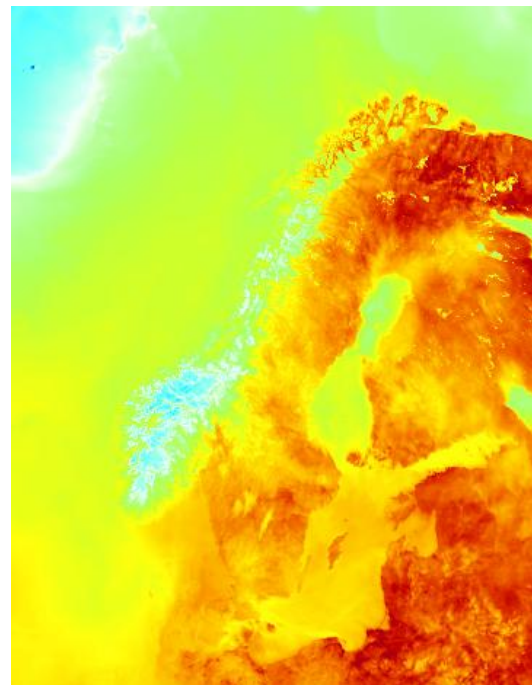
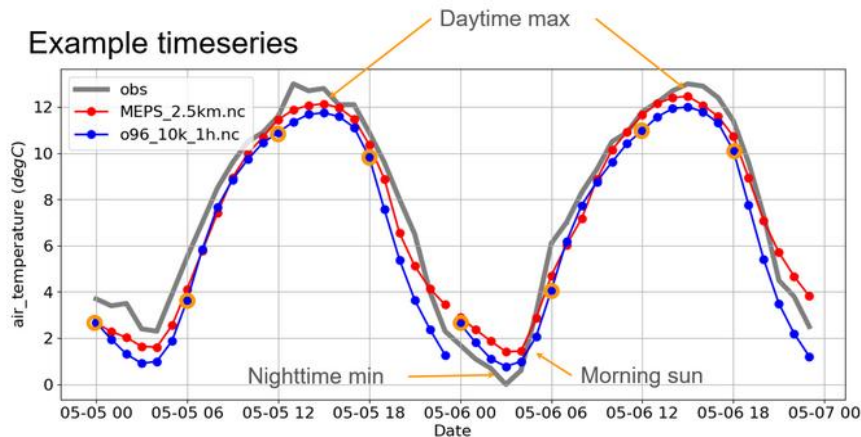






# Time Interpolator

- 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

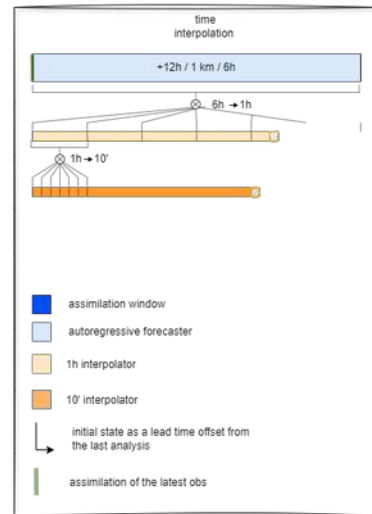
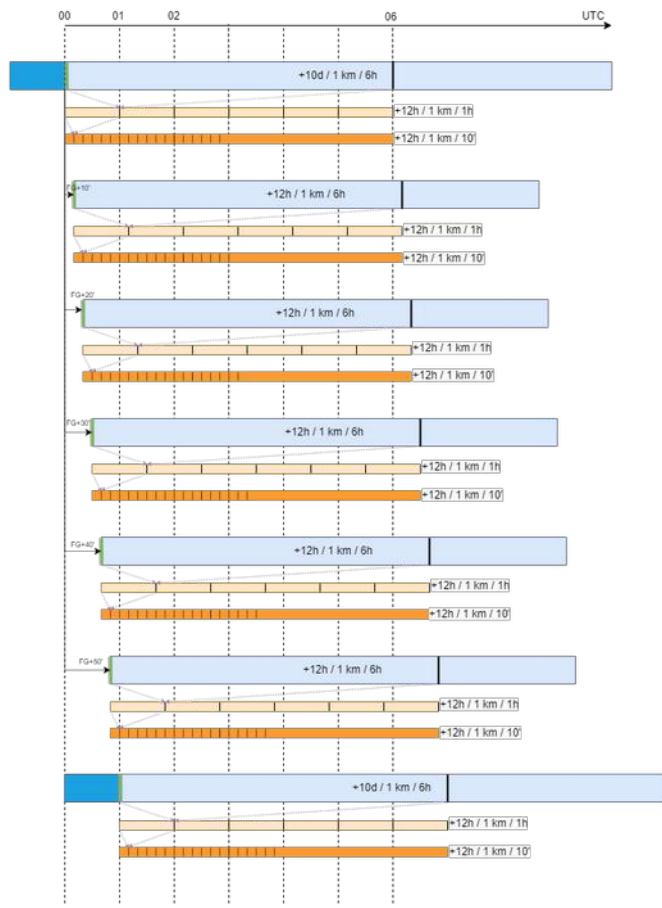


# Putting it together: Seamless RUC

## 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.
  - Anemoui: 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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