AI, meteorology & power system

AI-powered weather forecasting

Filip Grebenar

SPAIN HAS JUST 'FIVE DAYS' TO RESCUE WOBBLING POWER GRID – OR FACE RISK OF FRESH NATIONWIDE BLACKOUT, REGULATOR WARNS

'Self-consumption' in Spain refers to electricity that people or companies generate for their own use – for example, solar panels on a house, a block of flats, or a factory roof.

Instead of drawing power from the grid, they produce part (or all) of what they need themselves.

When there's lots of sunshine, thousands of these small rooftop systems cut demand on the main grid all at once.

Then, if clouds roll in or consumption patterns change, the grid sees sudden jumps up or down, creating unstable voltage.

The Importance of Weather Forecasting for Energy Markets

Weather is the state of the atmosphere with regards to wind, temperature, cloudiness, moisture, and pressure. Weather forecasting is the application of science to model, and thus predict, future conditions within the atmospheric system. From shorter term impacts of sudden temperature changes to mild winters leaving gas storage near full, weather is a consistent driver along the full spectrum of energy markets and contracts.

Article 44

Towards probabilistic risk assessment

4. By 31 December 2027, all TSOs shall jointly develop the methodology on common probabilistic risk assessment taking full account of the requirements of Article 75(1)(b) and Article 75(5) of the SO Regulation, and shall propose it as an amendment of this methodology in accordance with Article 7(4) of the SO Regulation. After its approval in accordance with Article 7 of the SO Regulation, the methodology on common probabilistic risk assessment shall form an annex to this methodology.

Accurate Weather Forecasting's Impact on Renewable Energy

In the rapidly evolving renewable energy industry, accurate weather data and forecasting have become crucial for optimizing operations, mitigating risks, and ensuring efficient energy production. As the effects of our changing atmosphere intensify, severe weather events are on the rise, making it imperative for leaders in the industry to stay ahead of the curve. Below we will discuss the increase of severe weather events, their impacts on the renewable energy industry, and how advancements in weather technology and forecasting can offer competitive advantages for companies.

Early Warning: Role of weather data in secure and reliable grid operation

February 26, 2022

Weather-related information is essential for day-to-day energy management as well as planning and maintenance of generation, transmission and distribution assets. Extreme events such as cyclones, floods and thunderstorms often have severe consequences for the electrical grid, such as supply disruptions for long durations and huge expenditure on restoration activities. To mitigate the impact of risks associated with weather and climate conditions, reliable weather forecasts are needed, which can reduce the uncertainty in supply and demand forecasts to a large extent. Accurate forecasting has become even more important with the increasing penetration of renewable energy sources into the grid. These are intrinsically intermittent in nature and highly dependent on weather conditions.

What meteorology has to offer?

In-situ weather measurements (e.g., anemometer, pyranometer, Doppler wind lidar)

Satellite observations (e.g., visible & infrared imagery, microwave sounders)

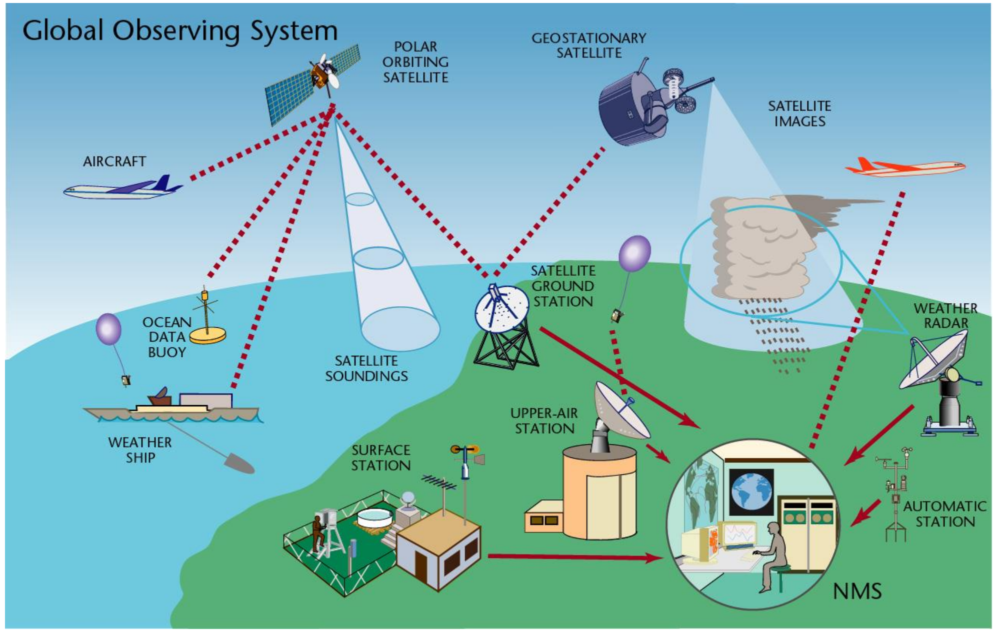
Radar data (e.g., precipitation intensity, reflectivity)

Lightning detection system (e.g., LINET sensors)

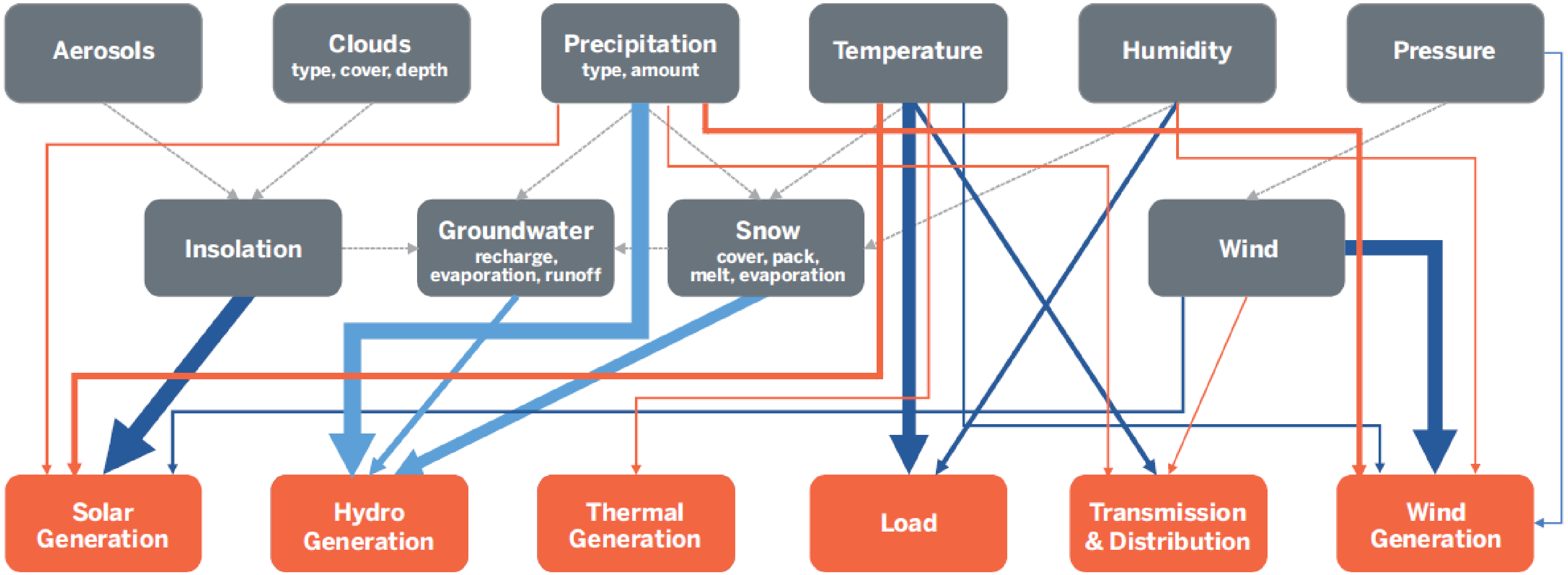
Weather forecasts (e.g., ECMWF, ICON, GFS)

Reanalysis data (e.g., ERA5, MERRA-2)

Climate projections (e.g., CMIP6, CORDEX)



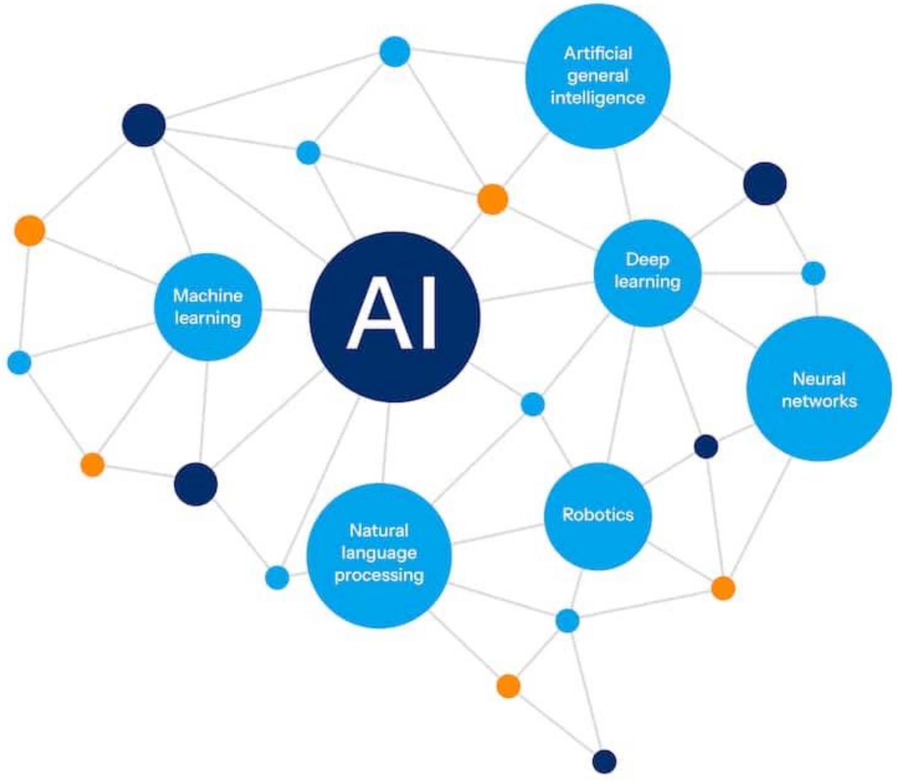
What power system needs?

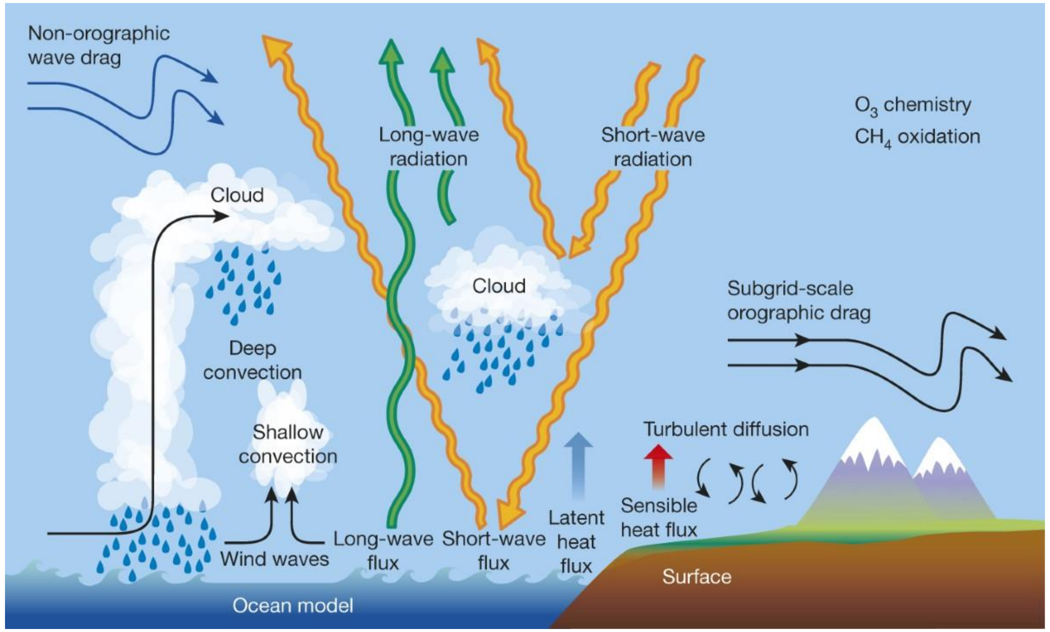


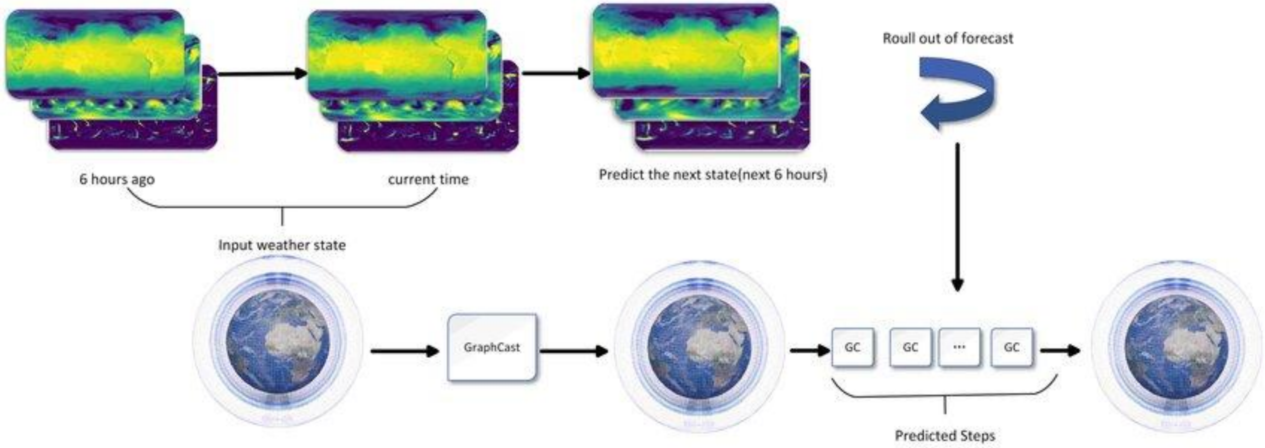
1. Solar power forecasting
2. Wind power forecasting
3. Hydropower forecasting
4. Electricity prices forecasting
5. Extreme weather forecasting
6. Electricity losses forecasting
7. Load forecasting
8. Grid system imbalance forecasting
9. Dynamic thermal rating
10. Asset management (e.g., real-time weather monitoring, vegetation management)
11. Power system resilience (e.g., wildfires-, storm-driven risk models)
12. Weather-based outage risk models (e.g., N-k calculation)
13. Estimation of distributed solar and wind generation without on-site measurements
14. Climate model projections for power system planning and resource adequacy

Where does AI fit in?

- NWP input data assimilation
- Data preprocessing
- NWP model parameters optimizations
- Nowcasting
- Extreme weather / hazard forecasting
- Short to medium-range weather forecasting
- Climate modelling & long-term projections
- Weather forecasts postprocessing
- Probabilistic weather forecasting





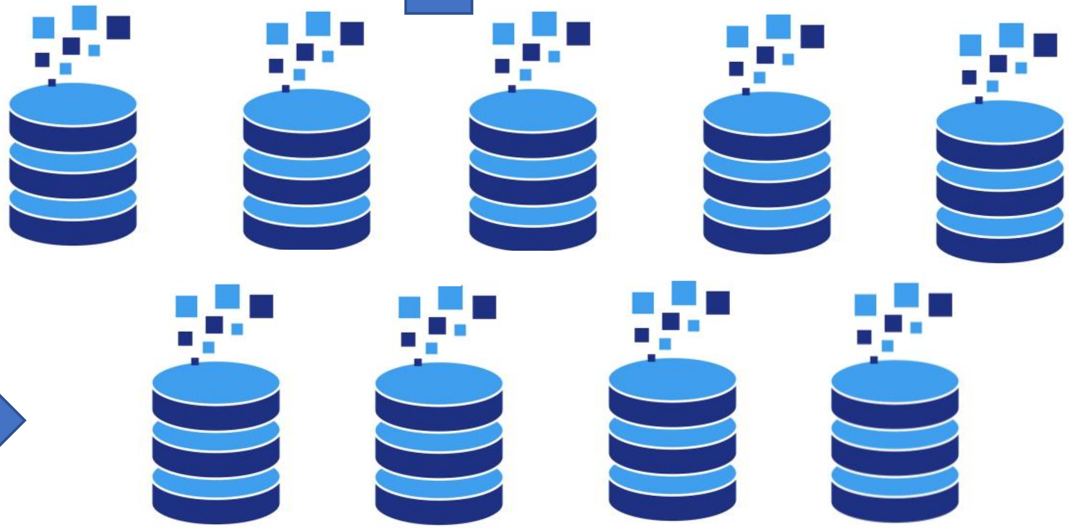


NWP

$$\frac{\partial u}{\partial t} = -u\frac{\partial u}{\partial x} - v\frac{\partial u}{\partial y} - w\frac{\partial u}{\partial z} - \frac{1}{\rho}\frac{\partial p}{\partial x} + f\,v + \nu\,\nabla^2 u$$

$$\frac{\partial v}{\partial t} = -u\frac{\partial v}{\partial x} - v\frac{\partial v}{\partial y} - w\frac{\partial v}{\partial z} - \frac{1}{\rho}\frac{\partial p}{\partial y} - f\,u + \nu\,\nabla^2 v$$

$$\frac{\partial w}{\partial t} = -u\frac{\partial w}{\partial x} - v\frac{\partial w}{\partial y} - w\frac{\partial w}{\partial z} + g + \nu\,\Delta w$$

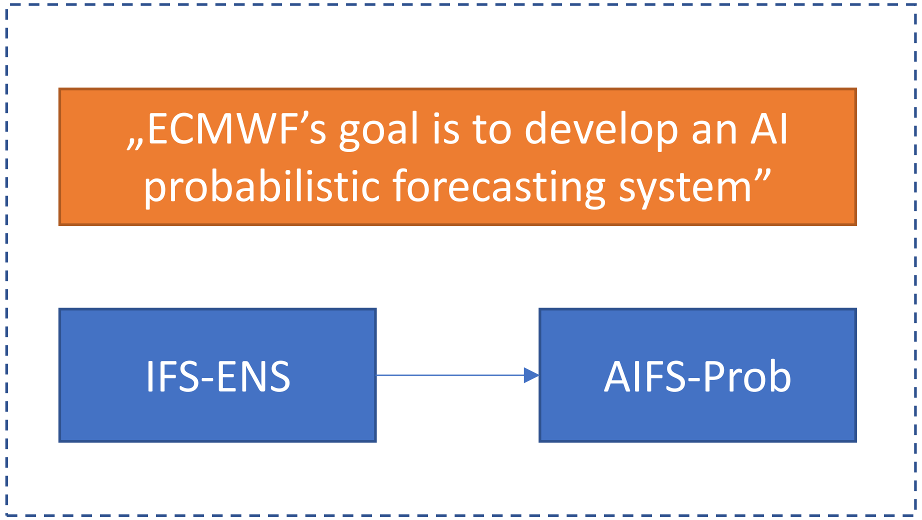


Rise of AI-driven weather forecasts

	Introduced	Name
Pathak et al.	2022	FourCastNet
Keisler	2022	-
Lam et al.	2023	GraphCast
Chen et al.	2023	Fuxi
Bi et al.	2023	Pangu-Weather
Molinaro et al.	2023	EPT-1
Nguyen et al.	2024	Stormer
Ben Bouallégue	2024	-
Lang et al.	2024	AIFS

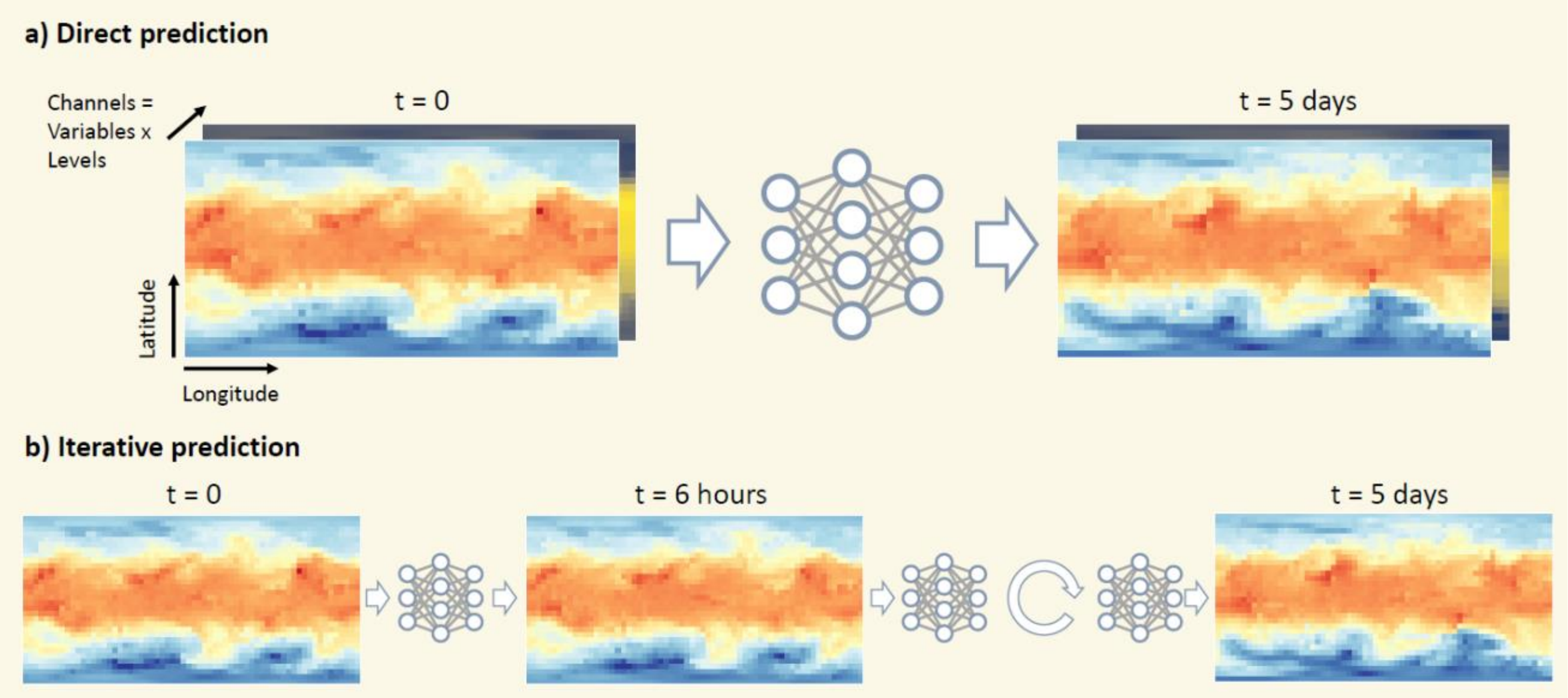
AIFS

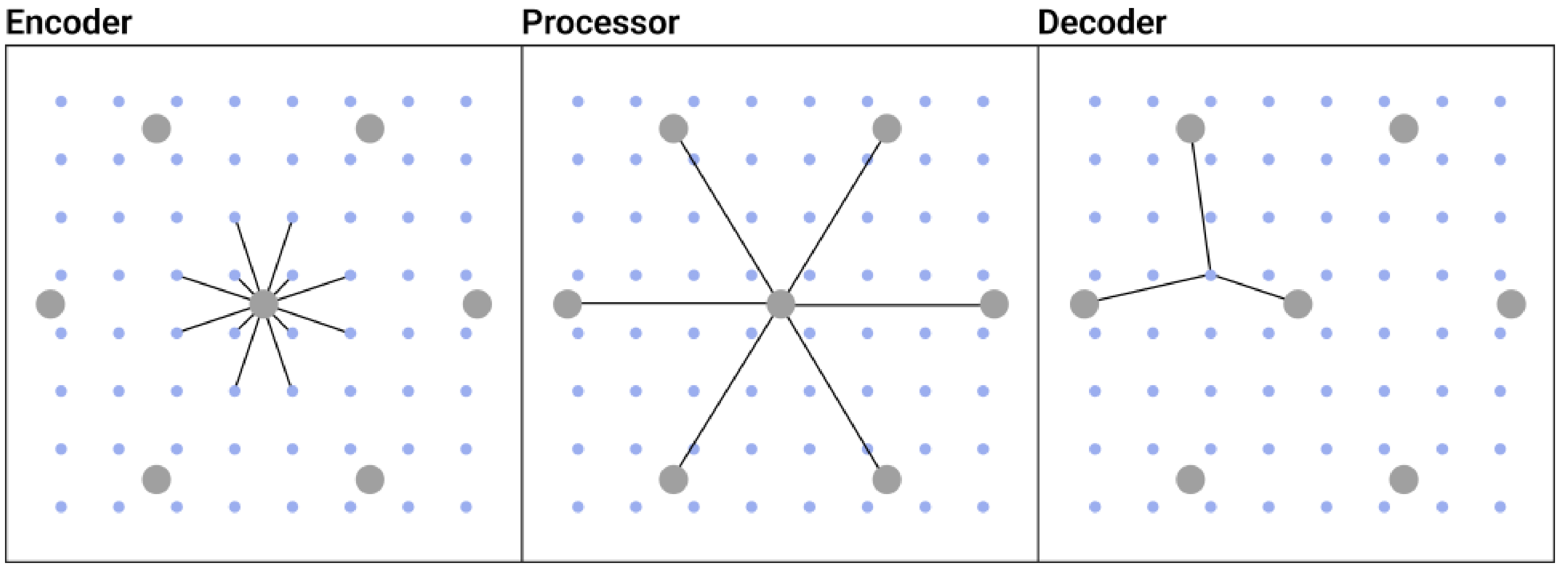
- Artificial Intelligence Forecasting System - ECMWF
- Python (PyTorch)
- October 2023
- Encoder-processor-decoder design
- 1° → 0.25° (Feb 2024)
- Autoregressive rollout during training
- 6-hour time steps, up to 360 h horizon
- MSE – loss function (area-weighted)
- All prognostic variables have roughly equal contributions to the loss
- Training duration: 1 week
- Running a 10 day forecast takes approximately **2 minutes 30 seconds** on a single A100 GPU, including the input and output of forecast data.
- 4x/day (open-data)



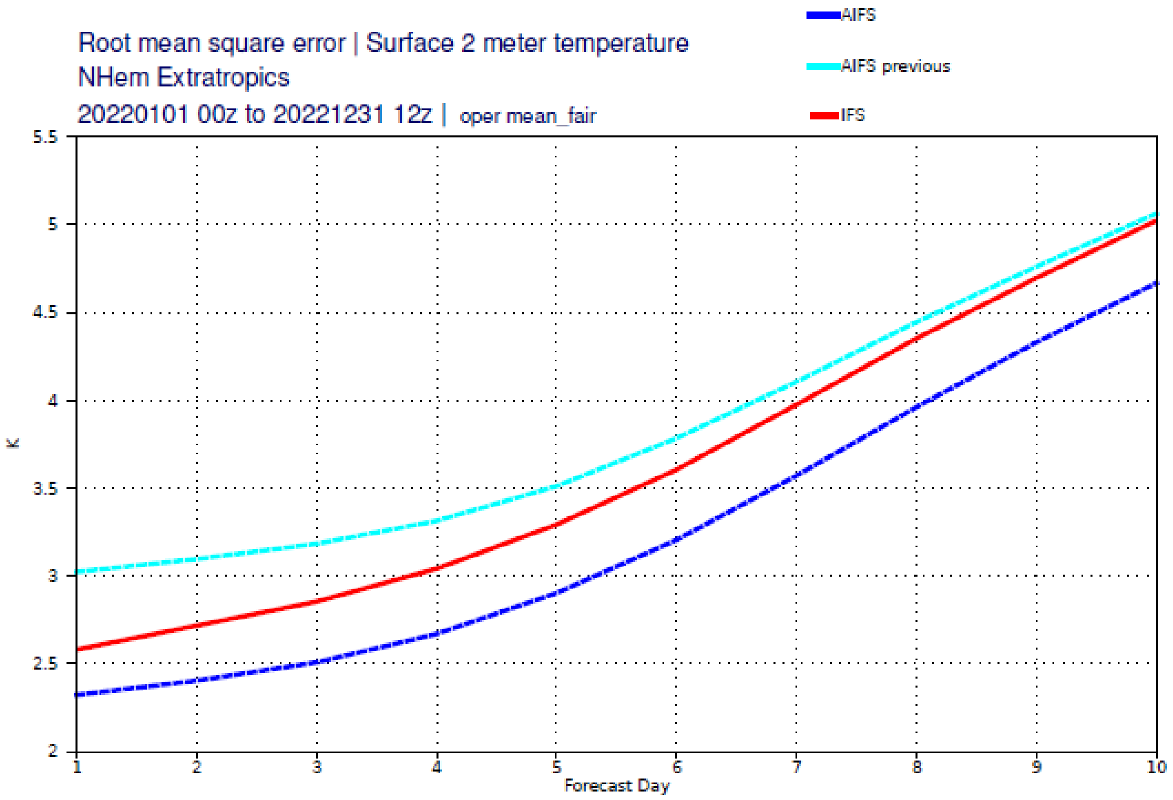
https://data.ecmwf.int/

AIFS


a) Direct prediction
Channels = Variables x Levels
t = 0
t = 5 days
Latitude
Longitude
b) Iterative prediction
t = 0
t = 6 hours
t = 5 days


Encoder
Processor
Decoder

AIFS


Root mean square error | Surface 2 meter temperature
NHem Extratropics
20220101 00z to 20221231 12z | oper mean_fair
AIFS
AIFS previous
IFS
K
5.5
5
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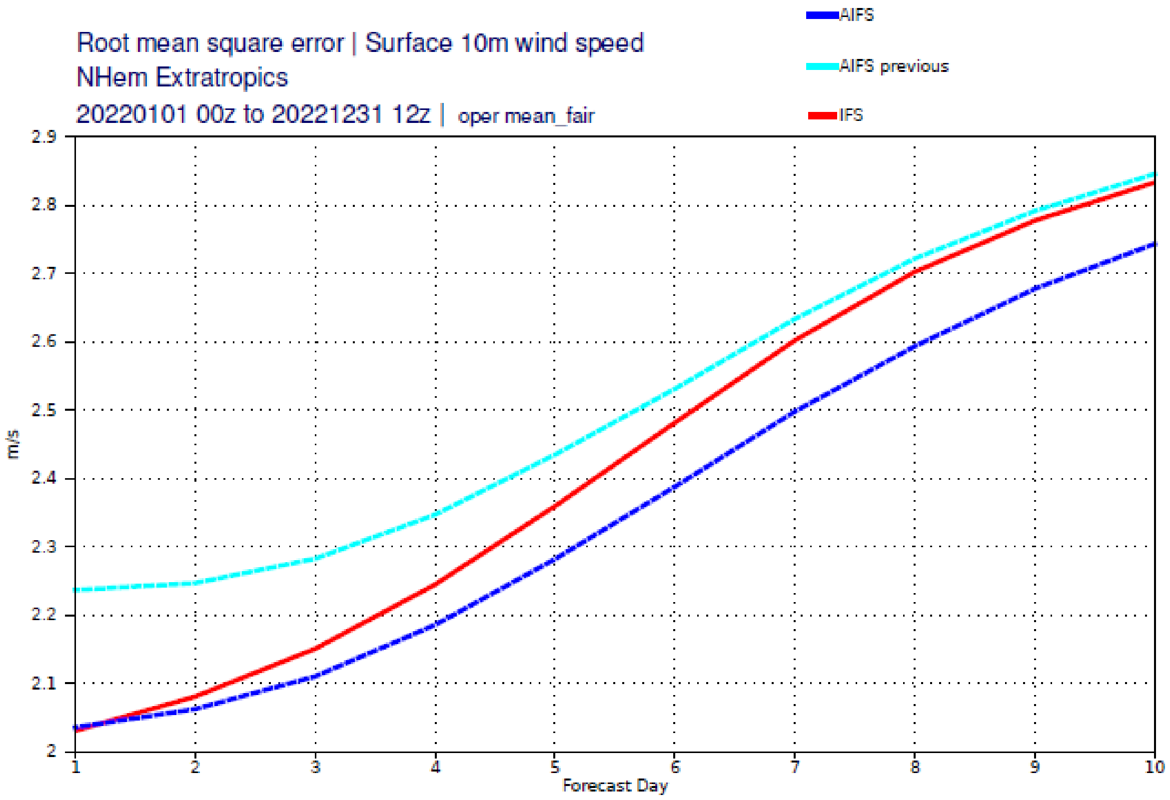
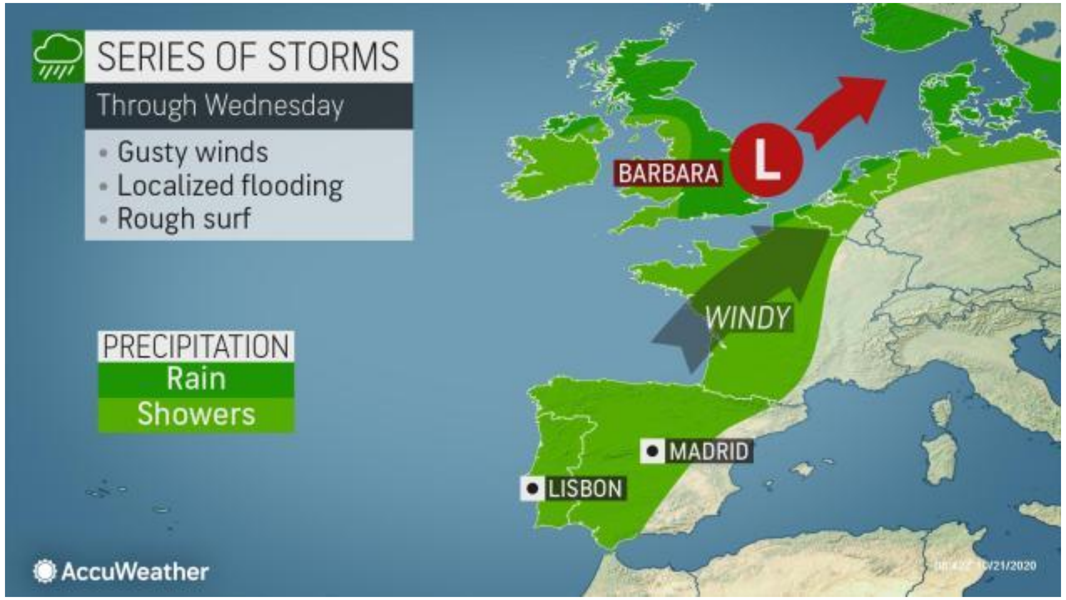
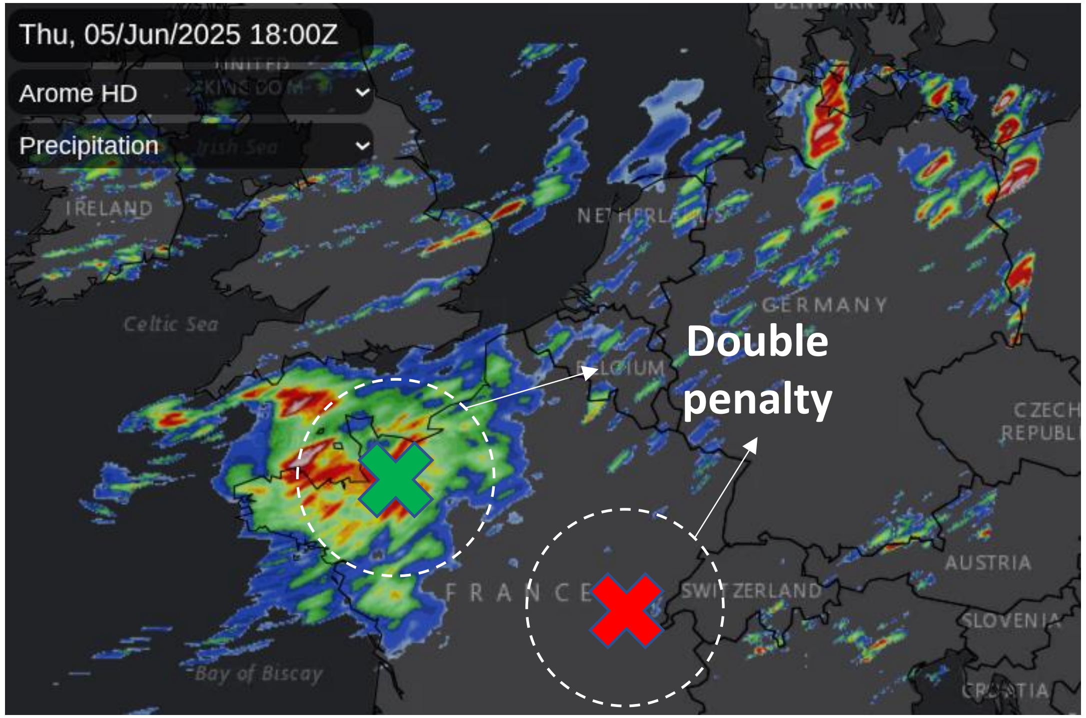
8
9
10
Forecast Day

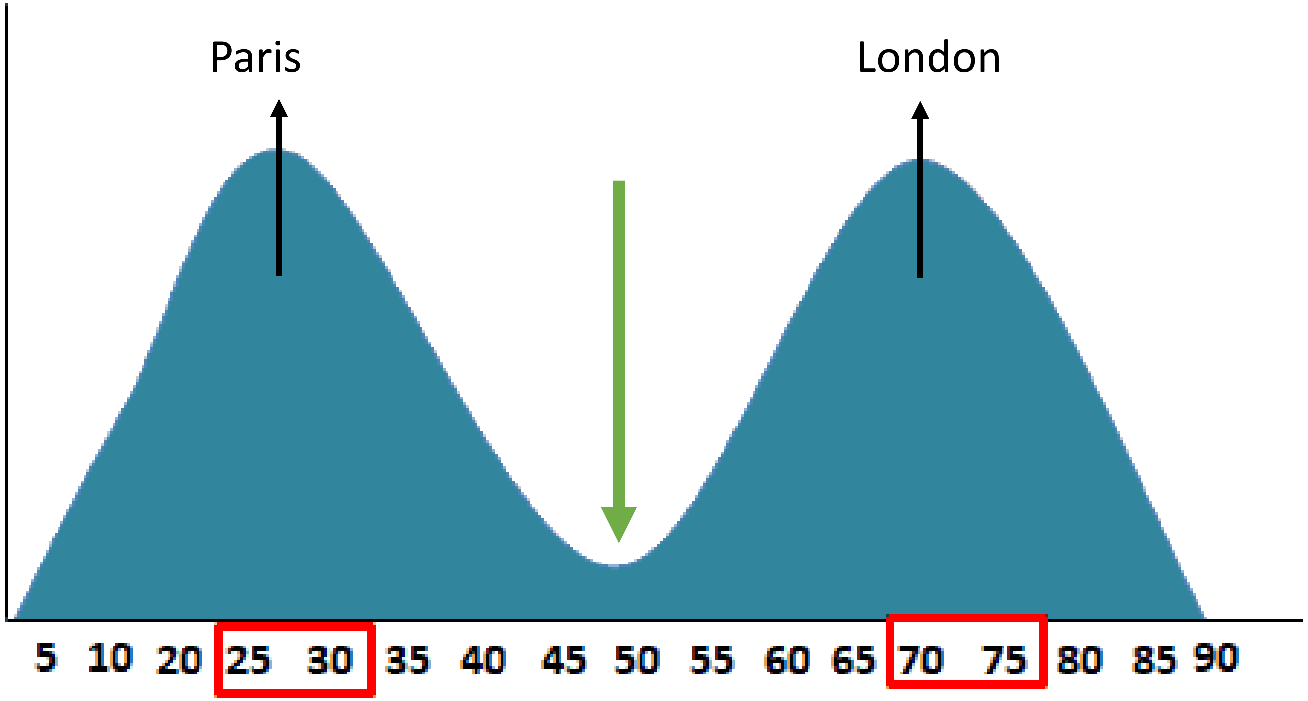

Root mean square error | Surface 10m wind speed
NHem Extratropics
20220101 00z to 20221231 12z | oper mean_fair
AIFS
AIFS previous
IFS
m/s
2.9
2.8
2.7
2.6
2.5
2.4
2.3
2.2
2.1
2
1
2
3
4
5
6
7
8
9
10
Forecast Day

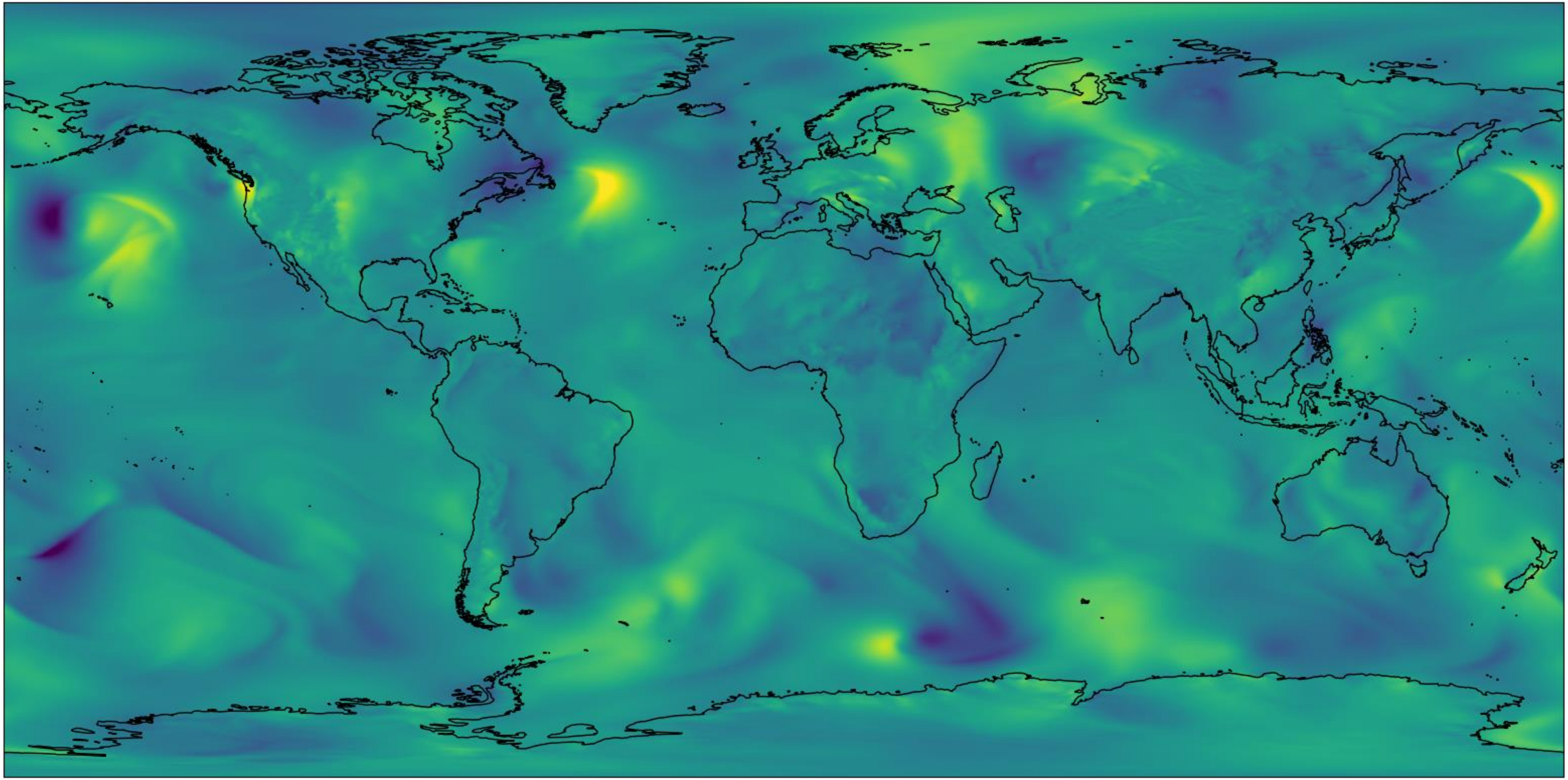
Blurring effect

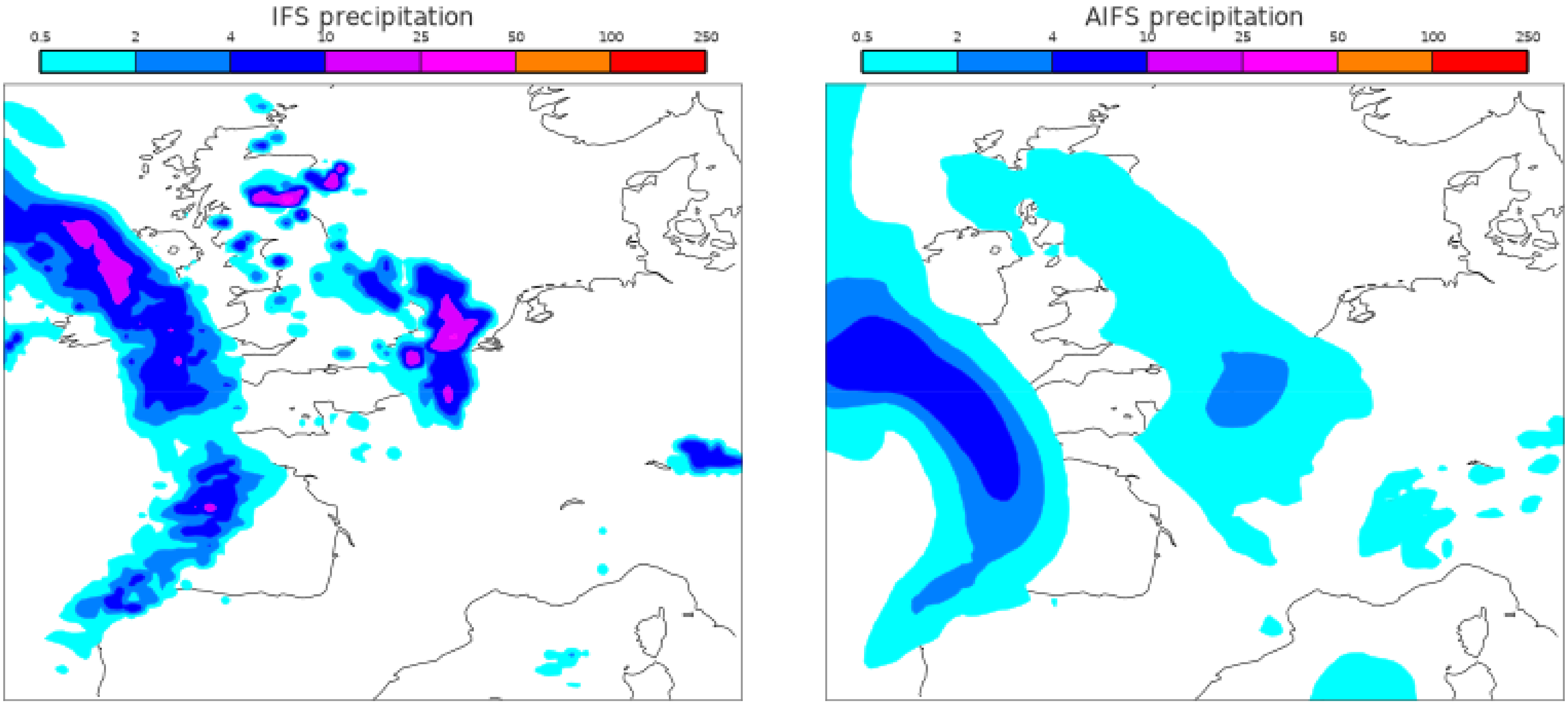
$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2$$










IFS precipitation
0.5
2
4
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25
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100
250
AIFS precipitation
0.5
2
4
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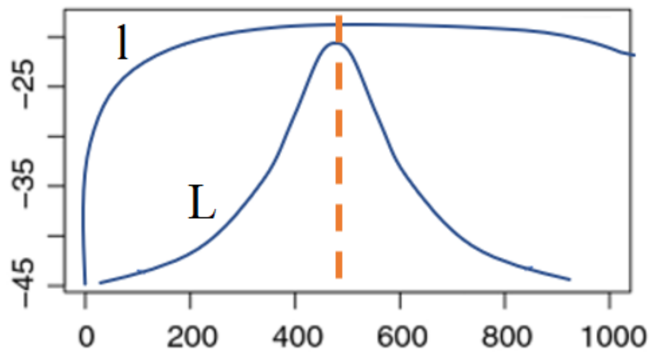
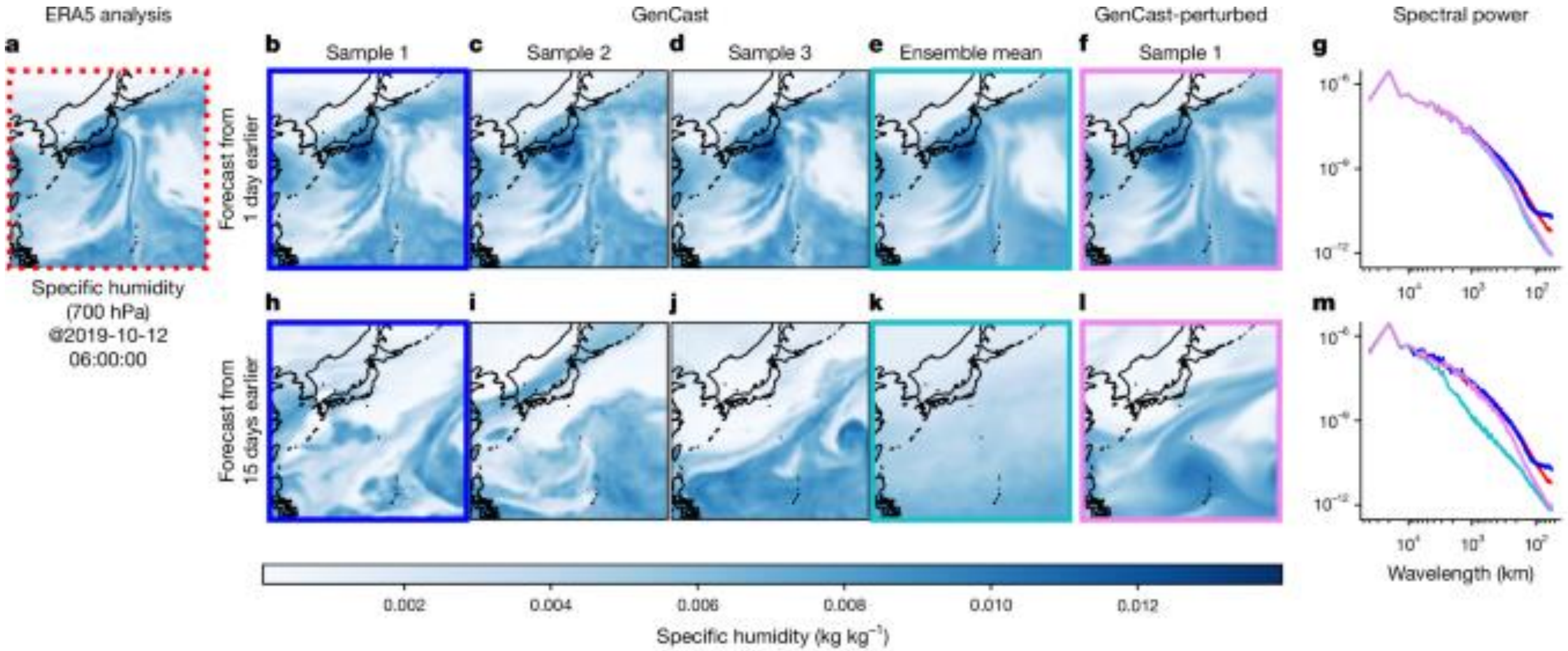
25
50
100
250

Log-likelihood function



$$\mathcal{L}_{\text{NLL}} = \frac{1}{2}\log\sigma^2 + \frac{1}{2}\frac{(y-\mu)^2}{\sigma^2}$$

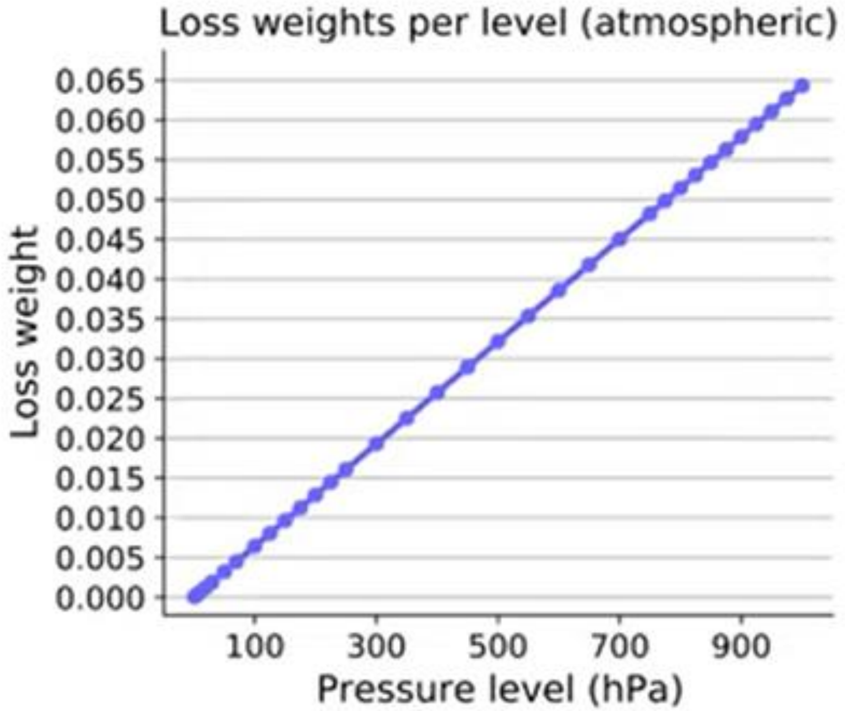


GraphCast

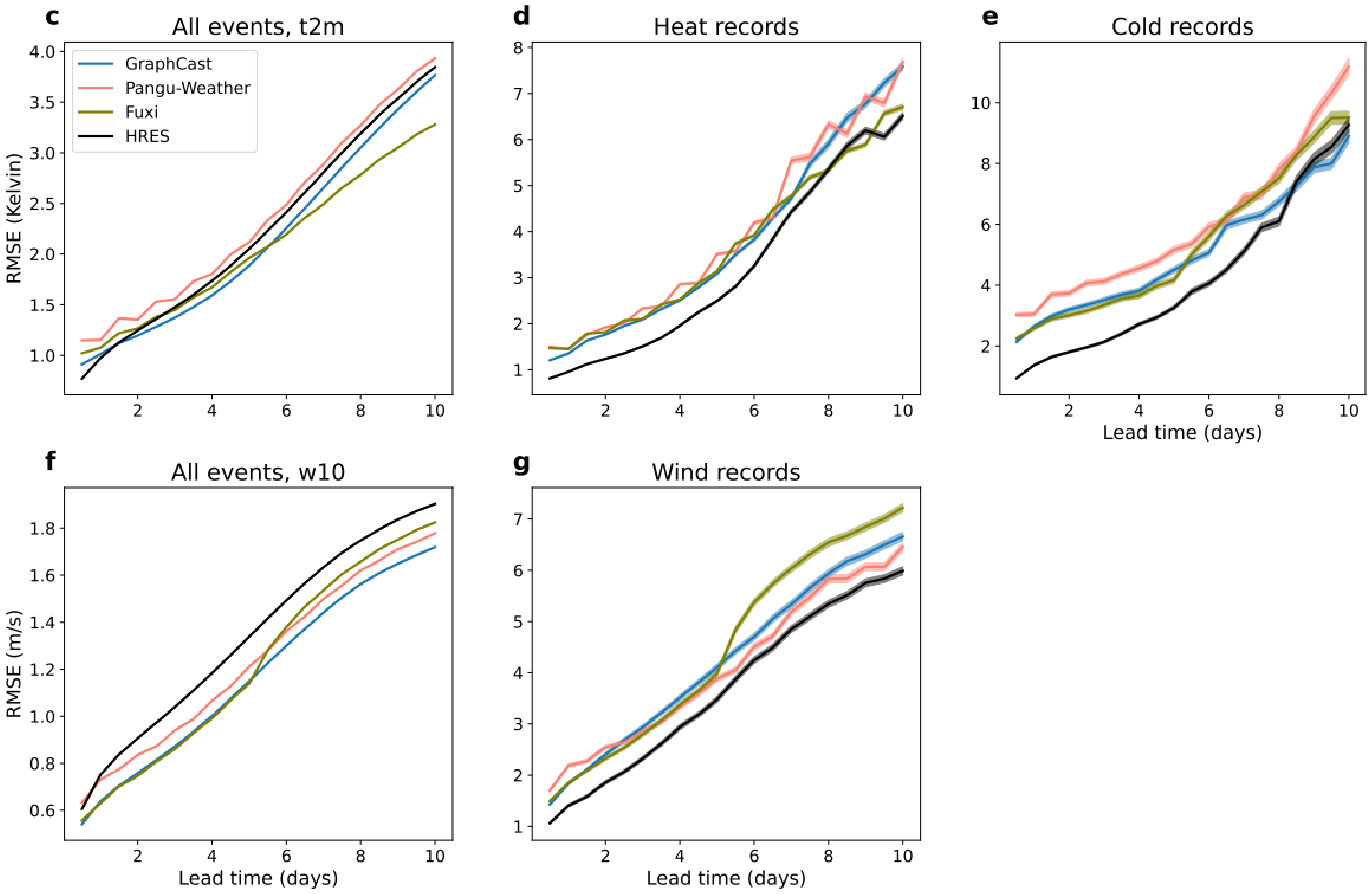
- 0.25° x 0.25° spatial resolution
  - 360 x 4 x 180 x 4 = 1440 x 720 = 1 036 800
- 6 atmospheric variables on 37 vertical levels + 5 surface variables
  - 37 x 6 + 5 = $\boxed{\text{227 variables}}$ → 90 % ↑
- 10 days ahead horizon at 6h time resolution
  - 10 x 4 = 40 frames

35 GB of data/run

- GNN-based
- <1min calculation time (on a single TPU v4 chip)
- 10-days ahead forecast
- 0.25°, 6h time resolution, 37 vertical levels
- Code & weights → GitHub

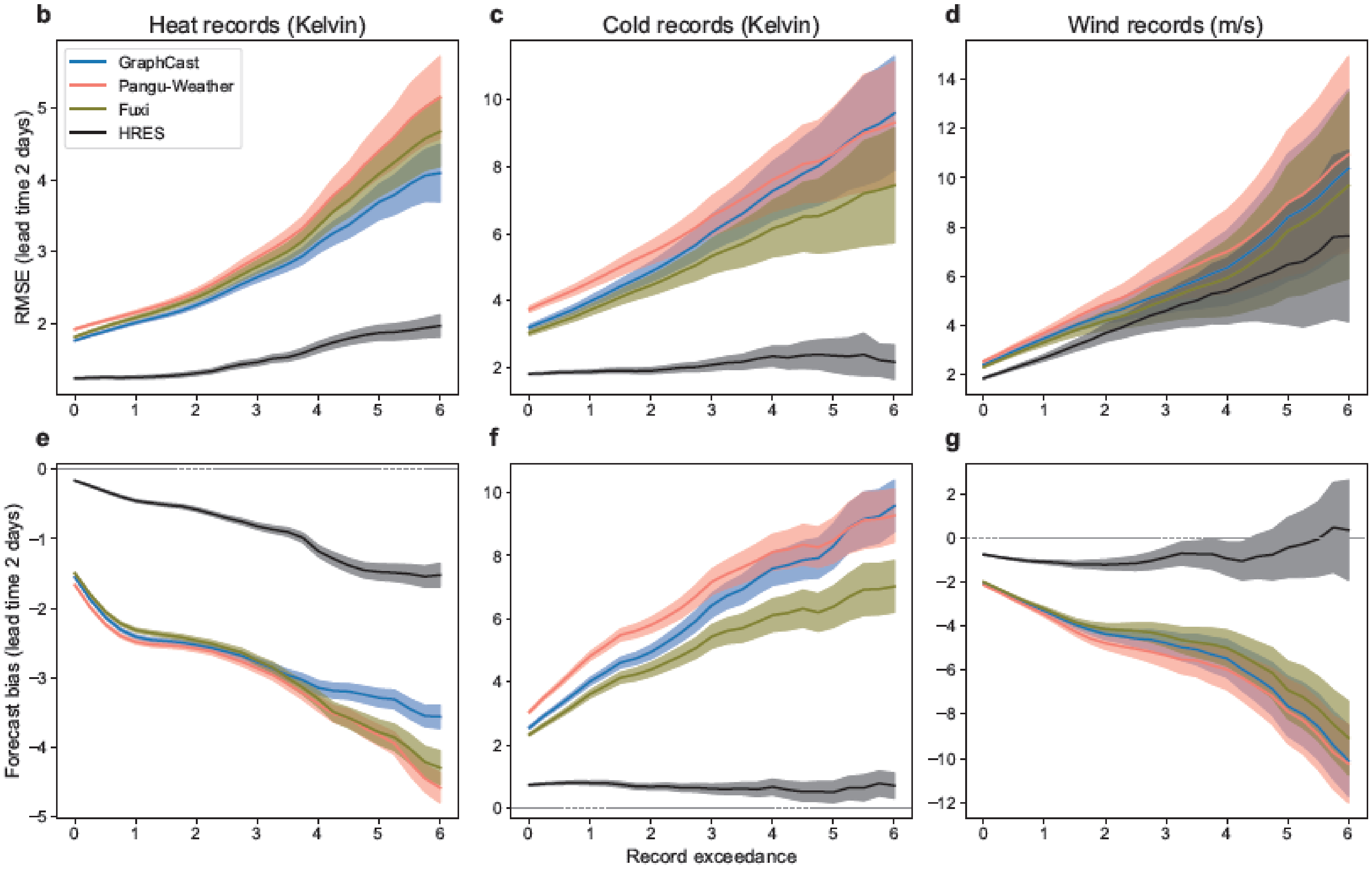


GraphCast

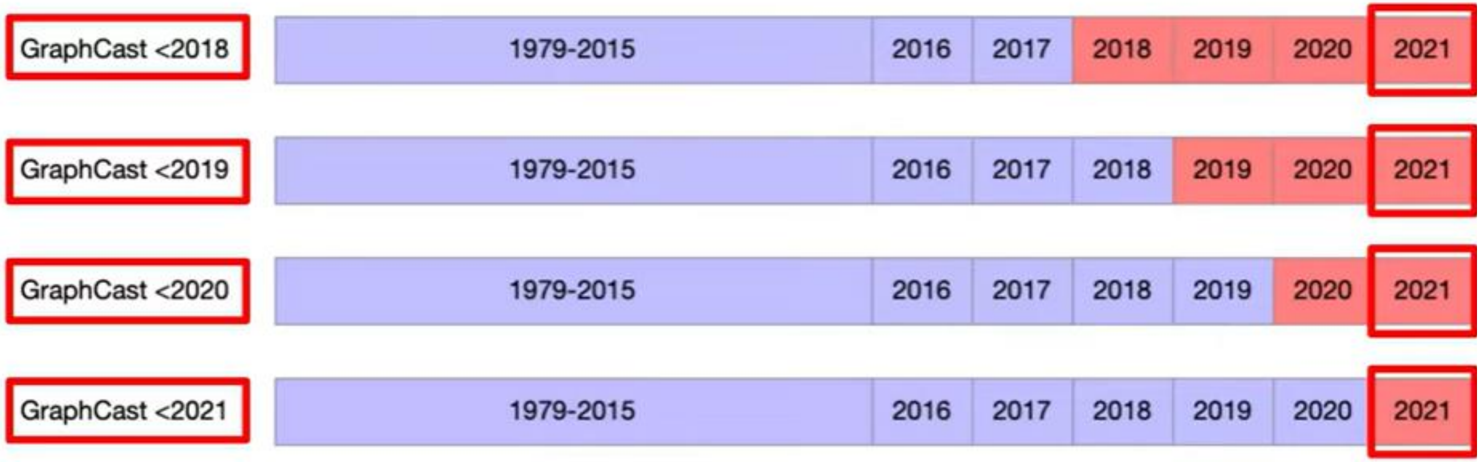


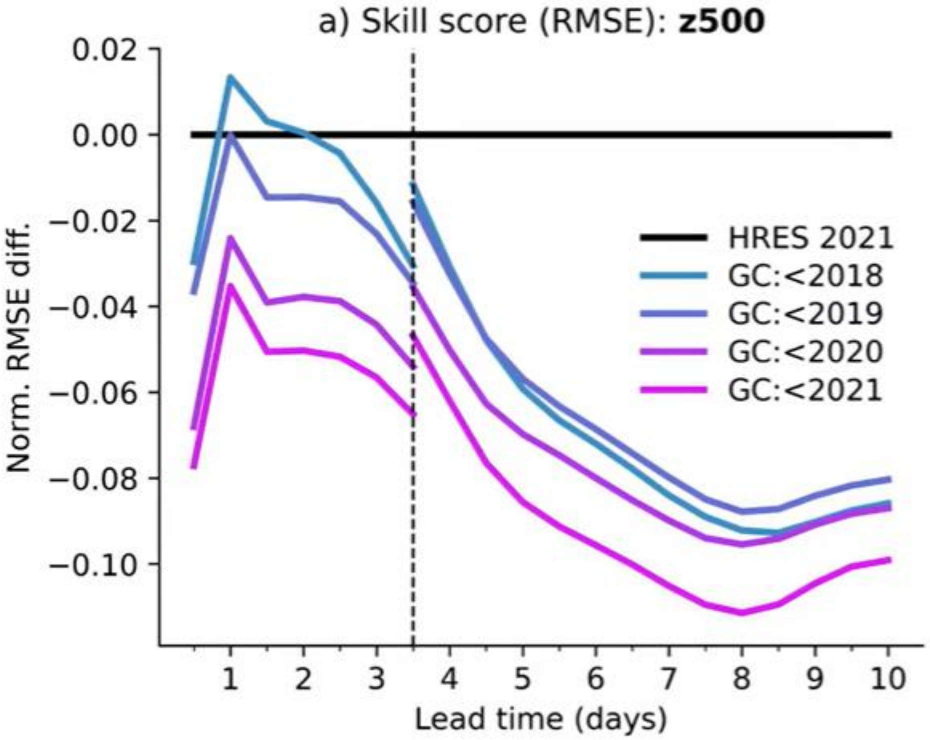
c
All events, t2m
GraphCast
Pangu-Weather
Fuxi
HRES
RMSE (Kelvin)
d
Heat records
e
Cold records
Lead time (days)
f
All events, w10
RMSE (m/s)
Lead time (days)
g
Wind records
Lead time (days)

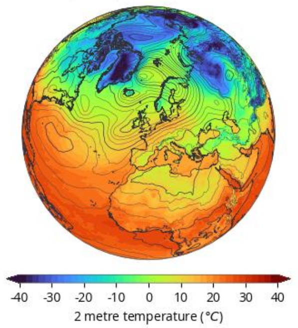
GraphCast – forecasting extremes



GraphCast – training set size effect







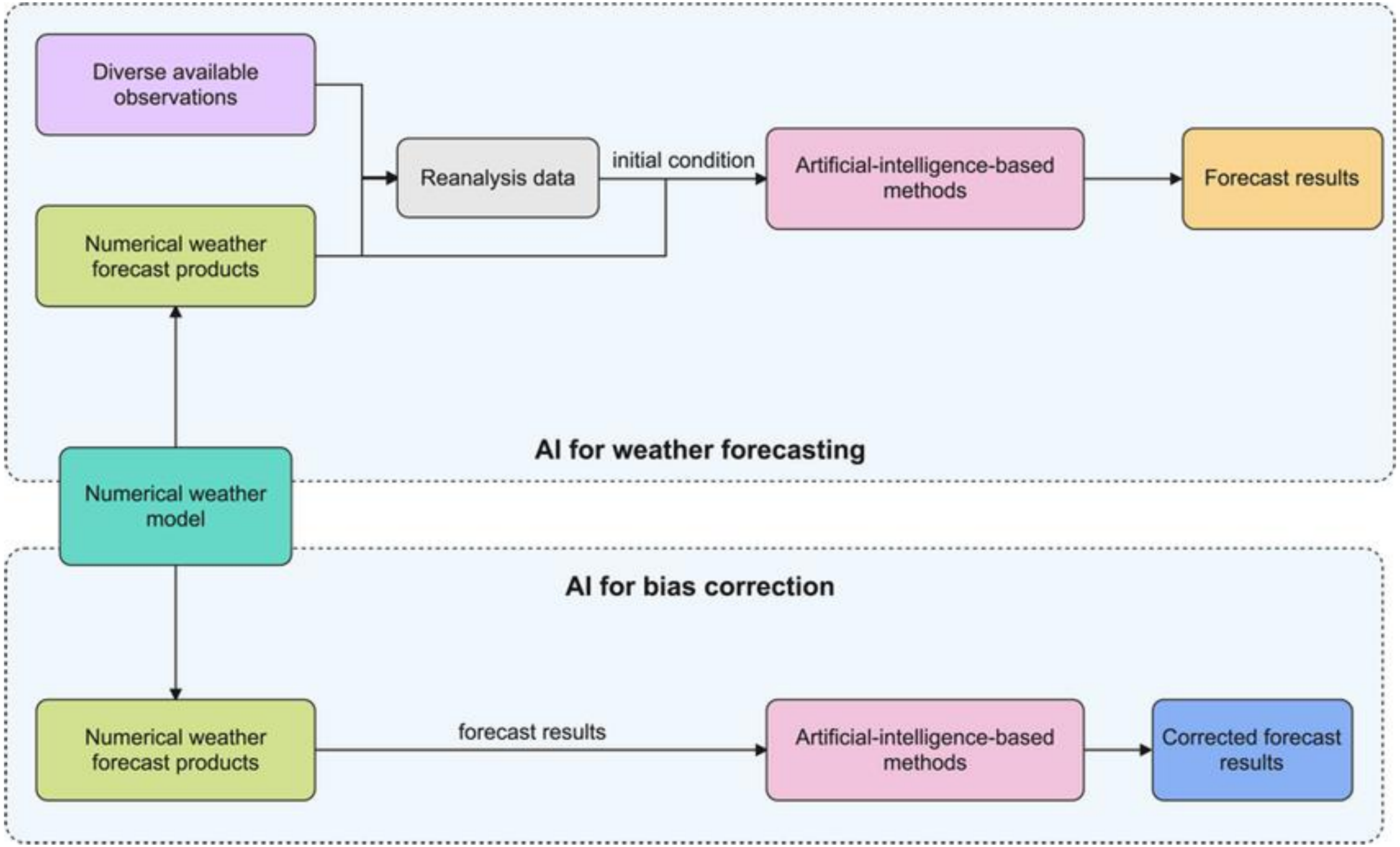
In common

- Training data: ERA5; > 1979 ~40 years (5-day delay: data latency, quality check, assimilation, post-processing) Copernicus
- Real-time forecasts: ECMWF 4D-Var
- Blurring of the forecast fields at longer lead times (MSE training objective) → „double penalty" – solutions are on the way
    - Optimization window size matters
- Problems with preserving physical coherence
- Out-of-distribution data (climate changes)

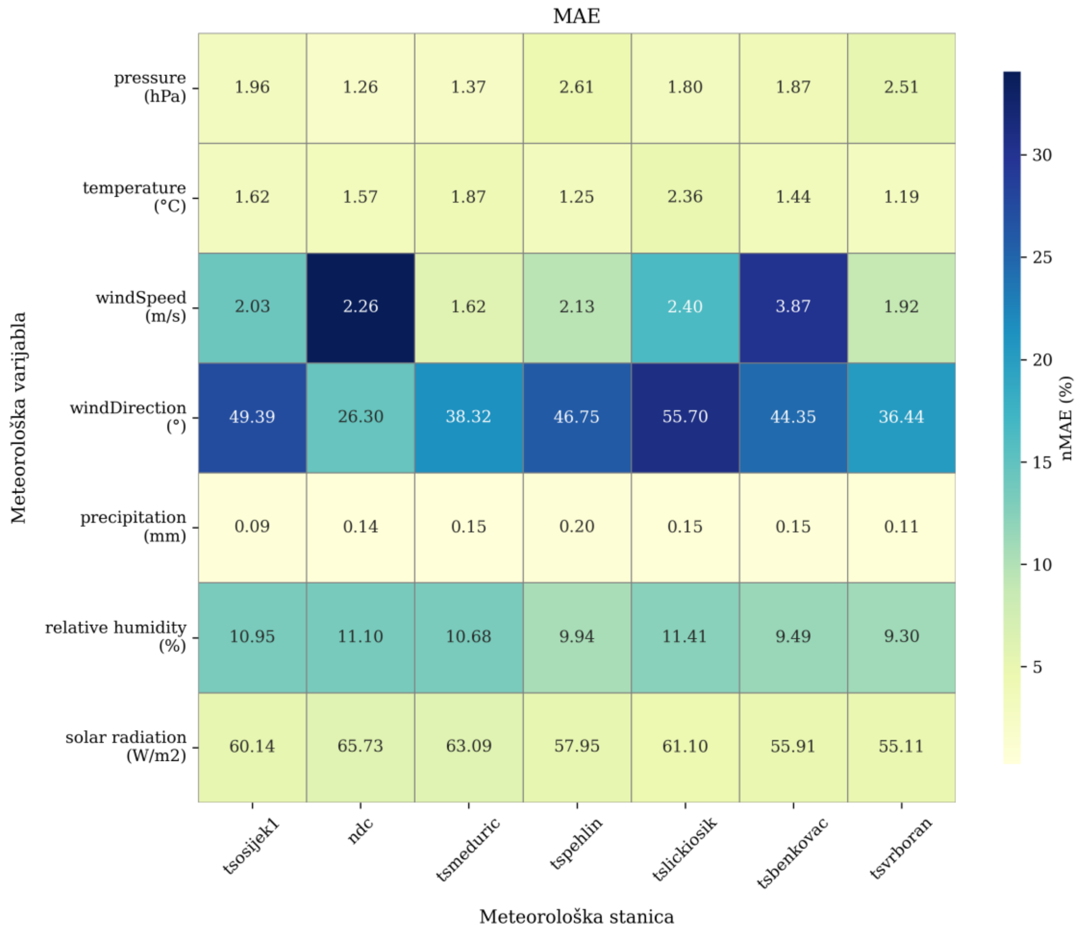
Outlook

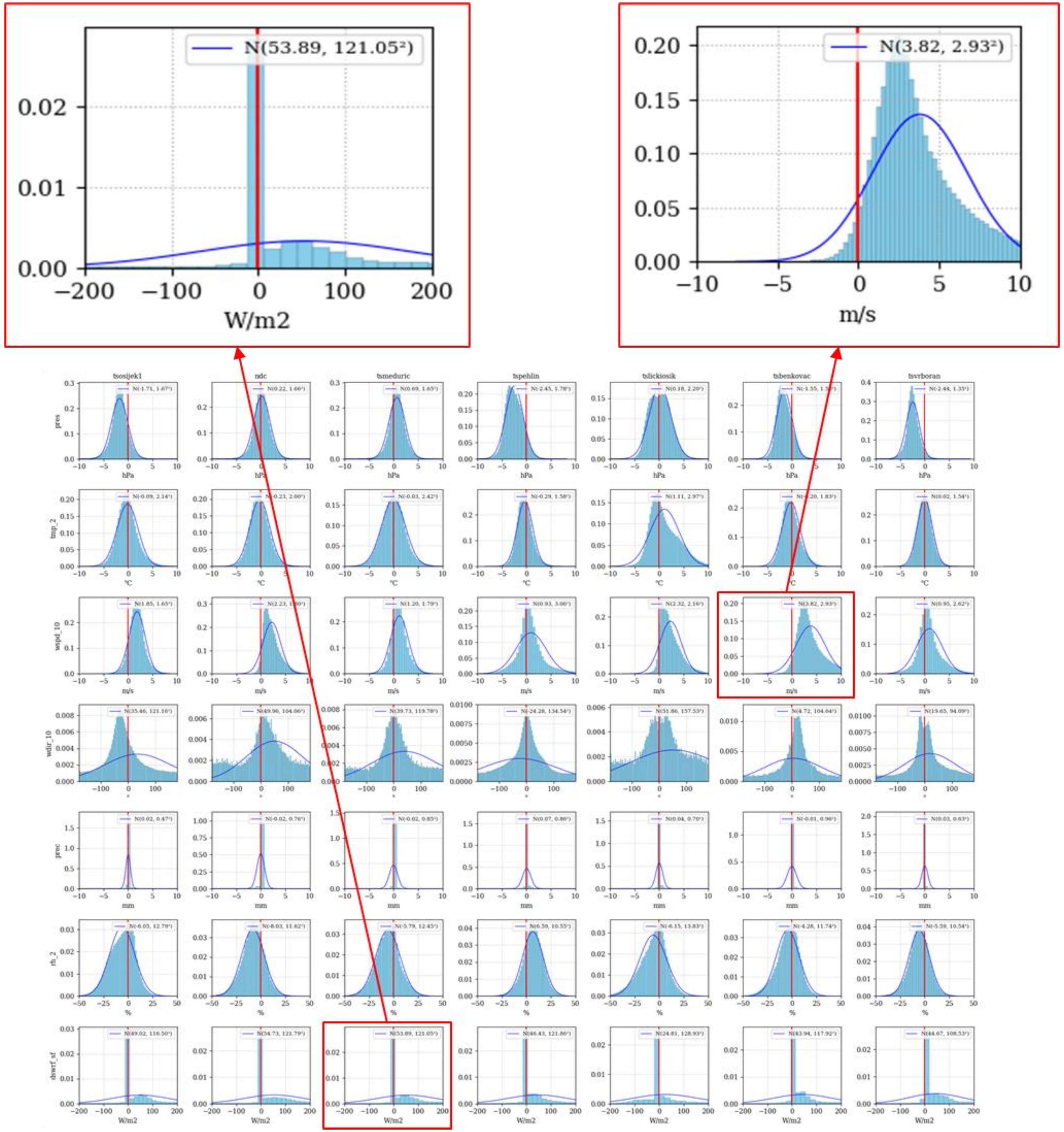
- Increase spatial resolution (0.25° currently)
- Increase temporal resolution (6h currently)
- Assimilating the observations directly (currently all rely on re-analysis)
- Probabilistic forecasts
- Better prediction of extreme weather events
- Increase training set size
- Physics-informed GNNs

Weather forecasting bias correction



Weather forecasting bias correction



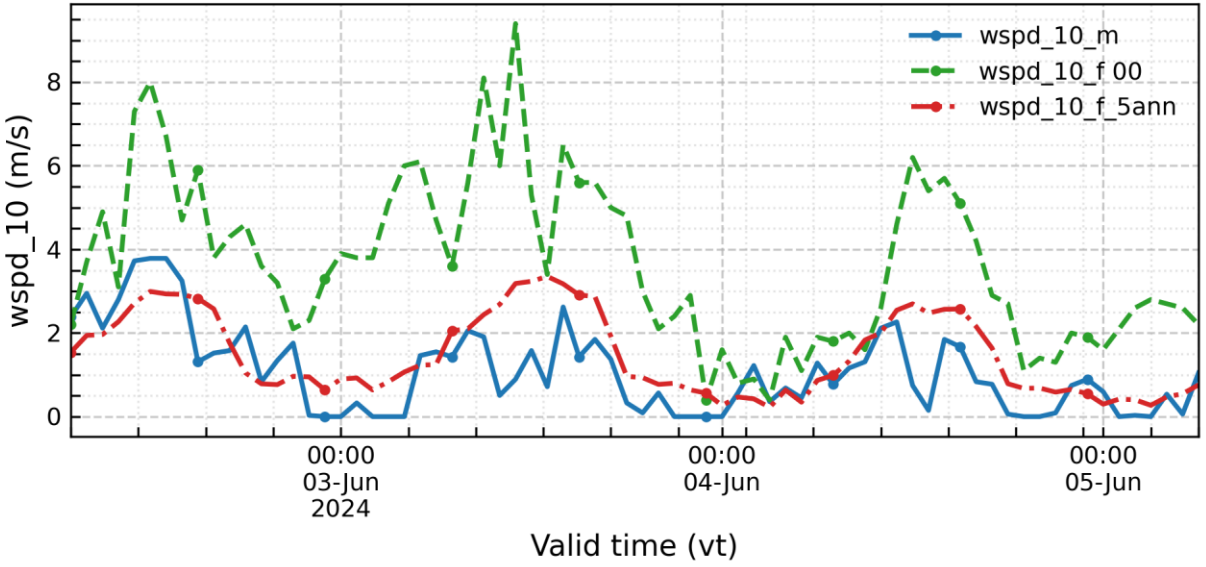


Weather forecasting bias correction

- BIAS
- DynBIAS
- LR
- SVR
- ANN

SS [%]	tsosijek1	ndc	tsmeduric	tspehlin	tslickiosik	tsbenkovac	tsvrboran
pres	43.8	15.9	23.7	60.5	38.8	49.2	66.4
tmp_2	15.2	3.6	21.4	13.2	20.7	10.5	9.4
wspd_10	56.8	80.5	42.1	30.1	69.4	78.9	30.5
wdir_10	13.1	17.0	15.8	22.3	/	9.7	26.7
prec	2.88	/	/	18.4	9.0	/	10.7
rh_2	45.8	42.8	34.7	42.4	49.2	23.5	28.5
dswrf_sf	32.0	31.5	25.6	23.8	1.7	20.7	29.2

tsbenkovac



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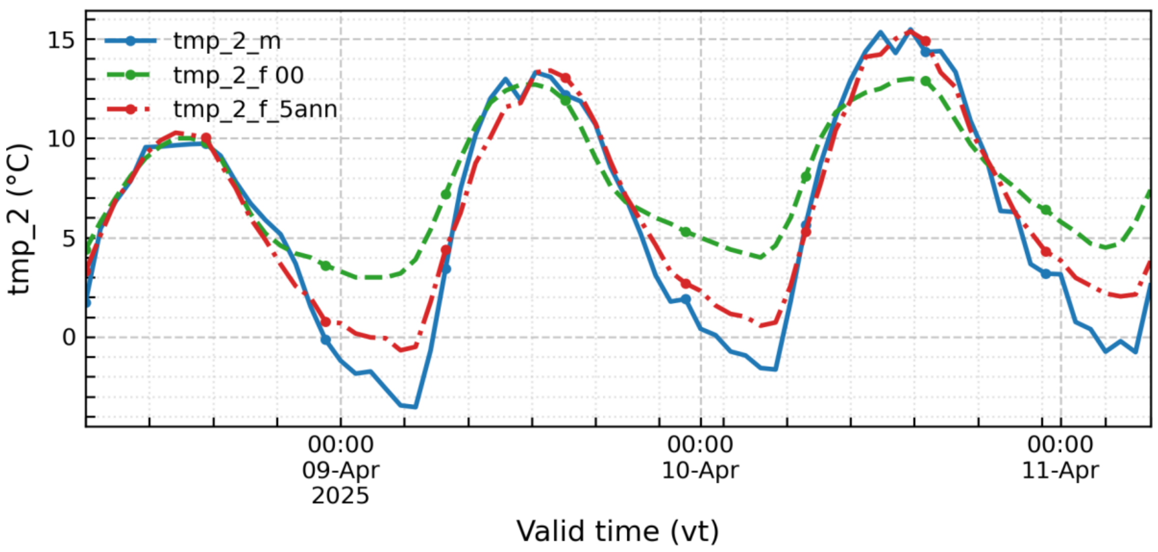

Implications for power system

- More accurate power system planning
- Increased frequency of producers/consumers plan changes
- Gate-closure lead time reduction (IDM)
- Open-source weather forecasting (accessibility, democratization)
- Better extreme weather forecasting (extending forecasting horizon)
- Early-warning systems (very short calculation time fosters that)
- Deterministic → probabilistic approach to forecasting

Fun fact…

Reaching JUPITER: ECMWF celebrates the first European exascale supercomputer

9 September 2025

Rank	System	Cores	Rmax (PFlop/s)	Rpeak (PFlop/s)	Power (kW)
1	**El Capitan** - HPE Cray EX255a, AMD 4th Gen EPYC 24C 1.8GHz, AMD Instinct MI300A, Slingshot-11, TOSS, HPE DOE/NNSA/LLNL United States	11,039,616	1,742.00	2,746.38	29,581
2	**Frontier** - HPE Cray EX235a, AMD Optimized 3rd Generation EPYC 64C 2GHz, AMD Instinct MI250X, Slingshot-11, HPE Cray OS, HPE DOE/SC/Oak Ridge National Laboratory United States	9,066,176	1,353.00	2,055.72	24,607
3	**Aurora** - HPE Cray EX - Intel Exascale Compute Blade, Xeon CPU Max 9470 52C 2.4GHz, Intel Data Center GPU Max, Slingshot-11, Intel DOE/SC/Argonne National Laboratory United States	9,264,128	1,012.00	1,980.01	38,698
4	**JUPITER Booster** - BullSequana XH3000, GH Superchip 72C 3GHz, NVIDIA GH200 Superchip, Quad-Rail NVIDIA InfiniBand NDR200, RedHat Enterprise Linux, EVIDEN EuroHPC/FZJ Germany	4,801,344	793.40	930.00	13,088

- Global Kilometer-scale Probabilistic Data-driven Modelling

THE END

Thank You for Your Attention!

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