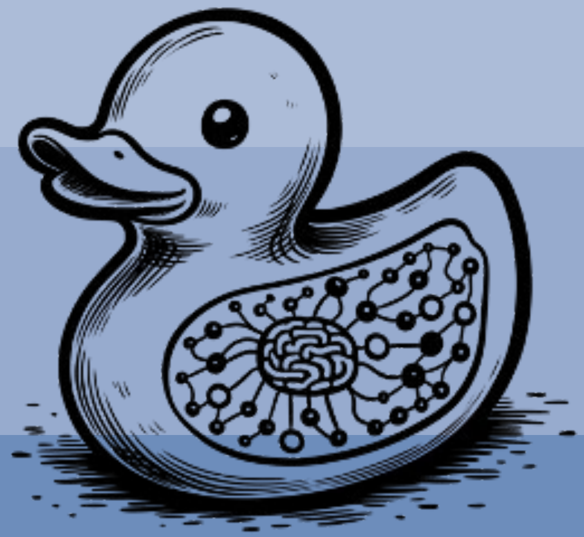
Ocean Model Development, Data-driven Parameterizations, and Machine Learning in Ocean Models of the Earth System Workshop

9-12 September 2024 – Boulder, Colorado

Towards a Fully Machine Learned Earth System Model at ECMWF



Lorenzo Zampieri & many colleagues

Ocean Modelling Team, Earth System Modelling, Research Dept.
lorenzo.zampieri@ecmwf.int

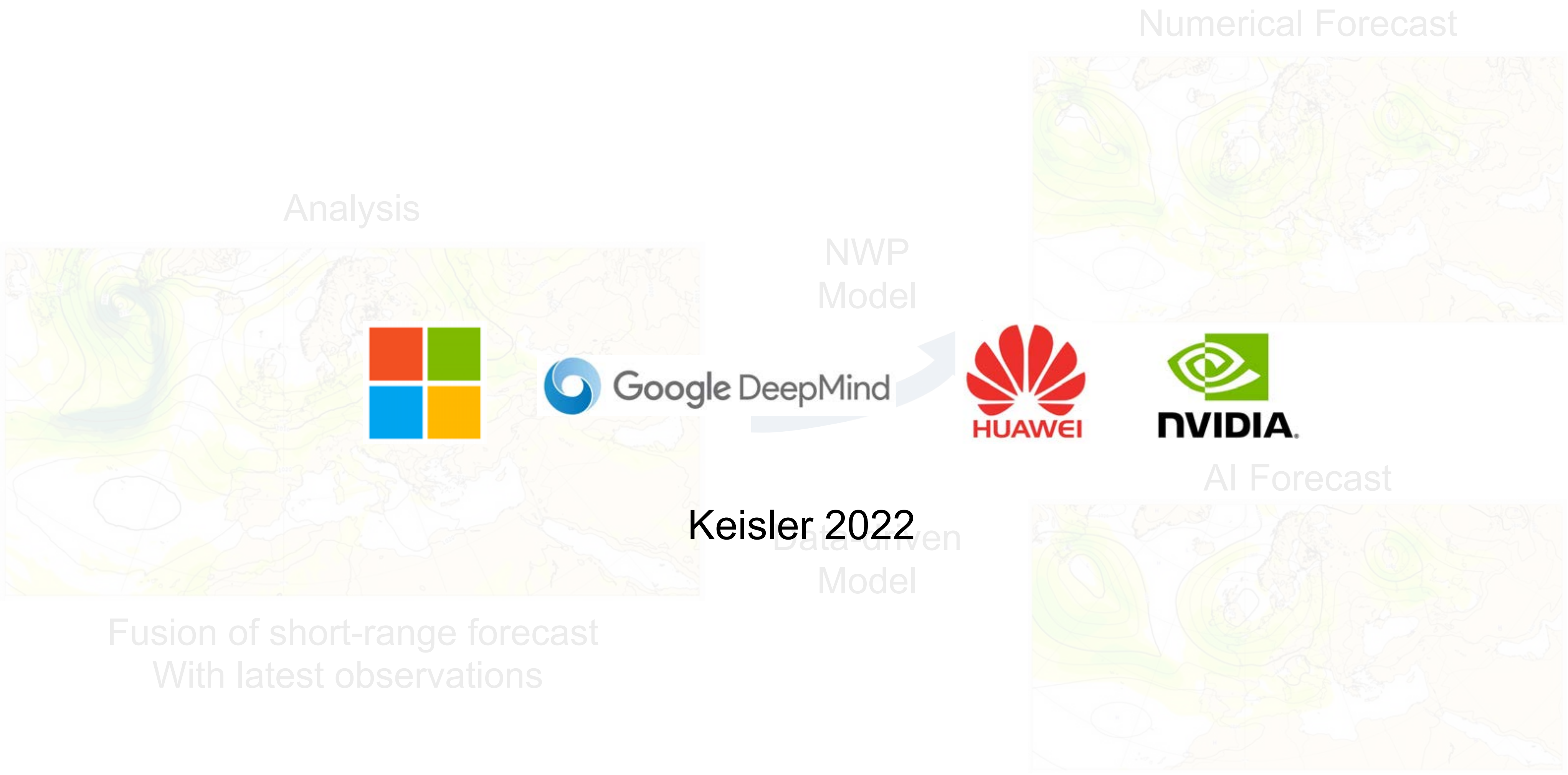
AIFS team: Rilwan Adewoyin, Mihai Alexe, Zied Ben Bouallègue, Matthew Chantry, Mariana Clare, Jesper Dramsch, Peter Dueben, Joffrey Dumont Le Brazidec, Rachel Furner, Sara Hahner, Simon Lang, Christian Lessig, Linus Magnusson, Michael Maier-Gerber, Gert Mertes, Gabriel Moldovan, Ana Prieto Nemesio, Cathal O'Brien, Florian Pinault, Jan Polster, Thomas Rackow, Baudouin Raoult, Mario Santa Cruz, Jakob Schloer, Helen Theissen, Steffen Tietsche, Lorenzo Zampieri

ECMWF EUROPEAN CENTRE FOR MEDIUM-RANGE WEATHER FORECASTS

Funded by the European Union

Destination Earth

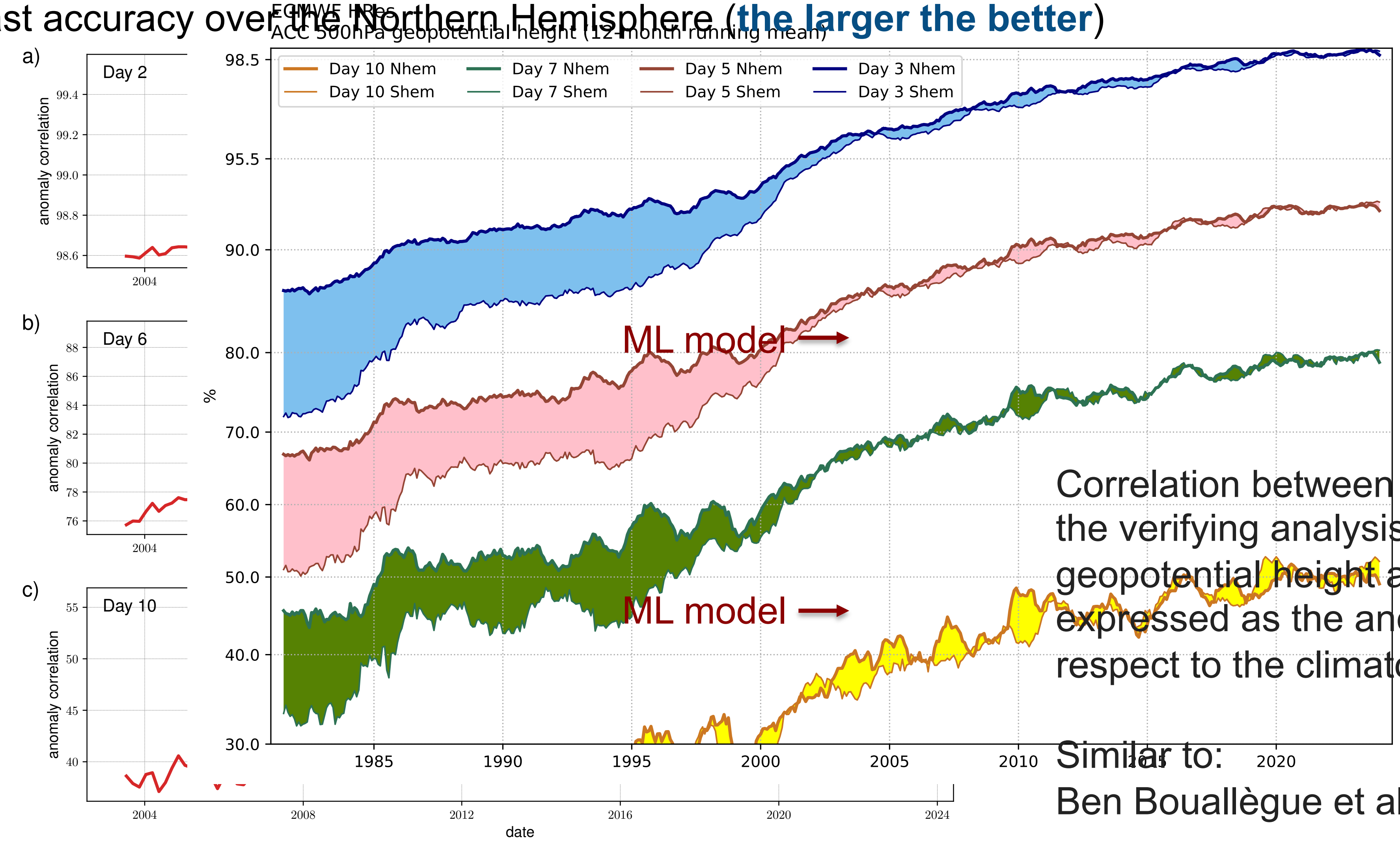
The Artificial Intelligence (AI) Revolution in Weather Forecasting



Keisler 2022

Skill of ML models in the context of the *“NWP Quiet Revolution”*

Forecast accuracy over the Northern Hemisphere (**the larger the better**)



Correlation between the forecasts and the verifying analysis for the geopotential height at 500 hPa, expressed as the anomaly with respect to the climatological height

Similar to:
Ben Bouallègue et al. (2024) BAMS

Skills of ML weather forecast models

		Pressure					Temperature					Humidity					Wind Vector				
		500hPa geopotential RMSE [kg²/m²]					850hPa temperature RMSE [K]					700hPa specific humidity RMSE [g/kg]					850hPa wind vector RMSE [m/s]				
	Lead time [days]	1	3	5	7	10	1	3	5	7	10	1	3	5	7	10	1	3	5	7	10
Physical models	IFS HRES	42	135	304	521	801	0.62	1.16	1.82	2.63	3.63	0.55	0.96	1.27	1.53	1.81	1.69	3.29	5.20	7.11	9.14
	IFS ENS Mean	42	132	277	439	621	0.65	1.11	1.62	2.17	2.80	0.51	0.84	1.06	1.22	1.38	1.63	2.98	4.44	5.74	6.94
	ERA5 Forecasts	43	142	316	534	811	0.59	1.19	1.87	2.68	3.66	0.53	1.01	1.33	1.59	1.86	1.63	3.40	5.37	7.26	9.23
ML / hybrid models	Pangu-Weather (oper.)	45	136	300	510	785	0.65	1.09	1.74	2.54	3.55	0.53	0.86	1.17	1.45	1.76	1.71	3.03	4.85	6.75	8.82
	GraphCast (oper.)	40	124	277	477	751	0.53	0.93	1.56	2.36	3.40	0.48	0.76	1.03	1.29	1.59	1.48	2.74	4.52	6.41	8.53
	Keisler (2022)	66	174	345	544	787	0.81	1.22	1.87	2.63	3.55	0.65	0.94	1.19	1.41	1.65	2.26	3.51	5.17	6.85	8.62
	Pangu-Weather	44	133	294	501	778	0.62	1.05	1.71	2.51	3.54	0.53	0.88	1.19	1.47	1.79	1.66	3.00	4.82	6.71	8.79
	GraphCast	39	124	274	468	731	0.51	0.94	1.56	2.33	3.36	0.47	0.79	1.06	1.30	1.59	1.42	2.76	4.44	6.22	8.17
	FuXi	40	125	276	433	631	0.54	0.97	1.59	2.14	2.91						1.47	2.80	4.49	5.64	7.02
	SphericalCNN	54	161	338	546	815	0.73	1.18	1.86	2.64	3.62	0.59	0.89	1.17	1.43	1.72	2.05	3.38	5.17	7.01	8.98
	NeuralGCM 0.7°	37	115	267	469	751	0.54	0.97	1.58	2.38	3.42	0.48	0.83	1.12	1.40	1.71	1.49	2.81	4.57	6.49	8.64
	NeuralGCM ENS Mean	43	126	266	424	606	0.65	1.02	1.53	2.10	2.75	0.54	0.81	1.02	1.19	1.37	1.76	2.88	4.28	5.59	6.83
	Climatology	820	820	820	820	820	3.44	3.44	3.44	3.44	3.44	1.59	1.59	1.59	1.59	1.59	7.89	7.89	7.89	7.89	7.89

−50 −20 −10 −5 −2 −1 1 2 5 10 20 50

Better ⟵ % difference in RMSE vs IFS HRES ⟶ Worse

From WeatherBench 2

https://sites.research.google/weatherbench/

Open Questions

How much is still to gain from ML techniques in weather forecasting?

Can we extend ML weather forecasting beyond the medium-range (15 days into the future)?

Can the same methodology be valuable also for other Earth system components?

Can we have a reliable ML model for climate?

Presentation Structure

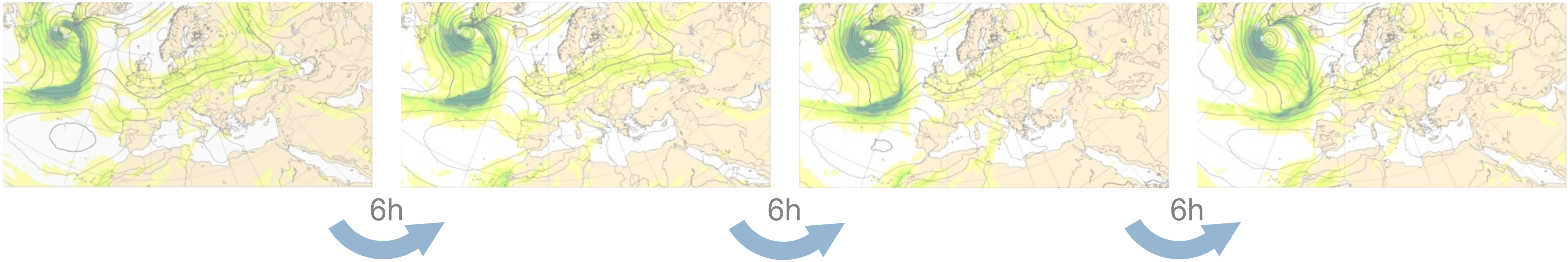
PART 1: ECMWF approach to medium-range weather forecasting with ML

PART 2: Exploratory work and future perspectives on non-atmospheric ML model components

AIFS – The Artificial Intelligence Forecast System

ECMWF's data-driven forecast model

TRAINING: The AI model learns from approximately 40 years of ECMWF's ERA5 reanalysis data, stepping 6h from analysis to analysis



For forecasting, we autoregressively step the trained model 6h into the future $x_n = f(x_{n-1})$

Similar approach followed by many research groups and tech companies
(Google Deepmind, NVIDIA, Keisler, Huawei, …)

AIFS – The Artificial Intelligence Forecast System

ECMWF's data-driven forecast model

CURRENT MODEL DESIGN:

Updated at the beginning of 2024 – **~0.25° resolution**

- Attention based GNN for encoder/decoder
- Transformer backbone in the processor
- Trained in ~1 week on 64 GPUs

AIFS - ECMWF'S DATA-DRIVEN FORECASTING SYSTEM

A PREPRINT

Simon Lang* Mihai Alexe* Matthew Chantry Jesper Dramsch Florian Pinault Baudouin Raoult

Mariana C. A. Clare Christian Lessig Michael Maier-Gerber Linus Magnusson

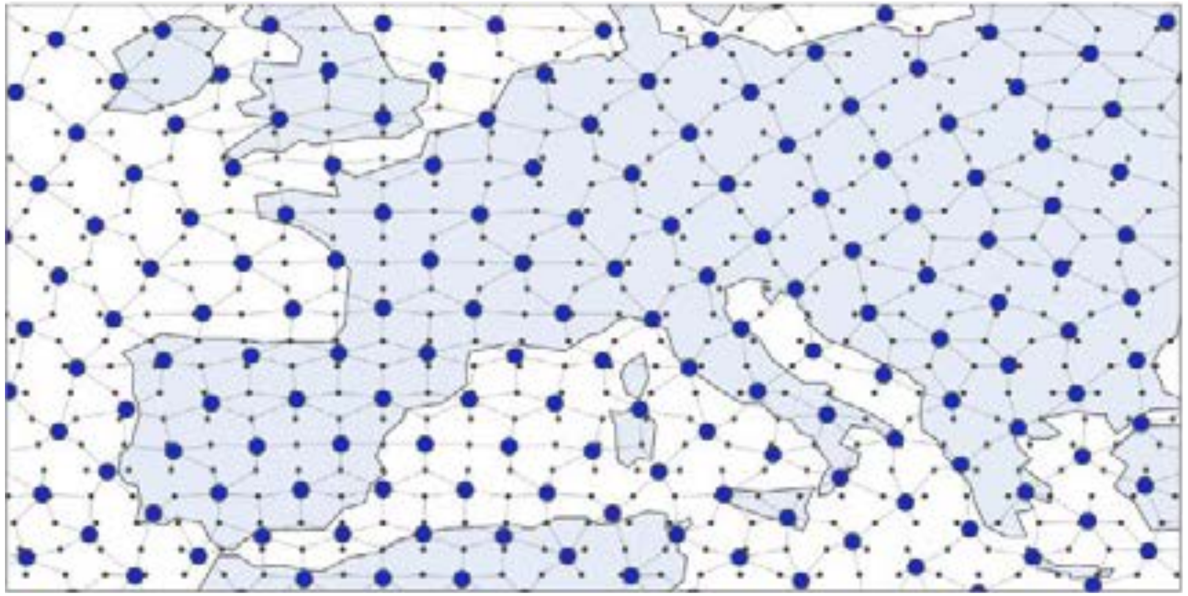
Zied Ben Bouallègue Ana Prieto Nemesio Peter D. Dueben Andrew Brown Florian Pappenberger

Florence Rabier

May 2024

AIFS – The Encoder and Decoder

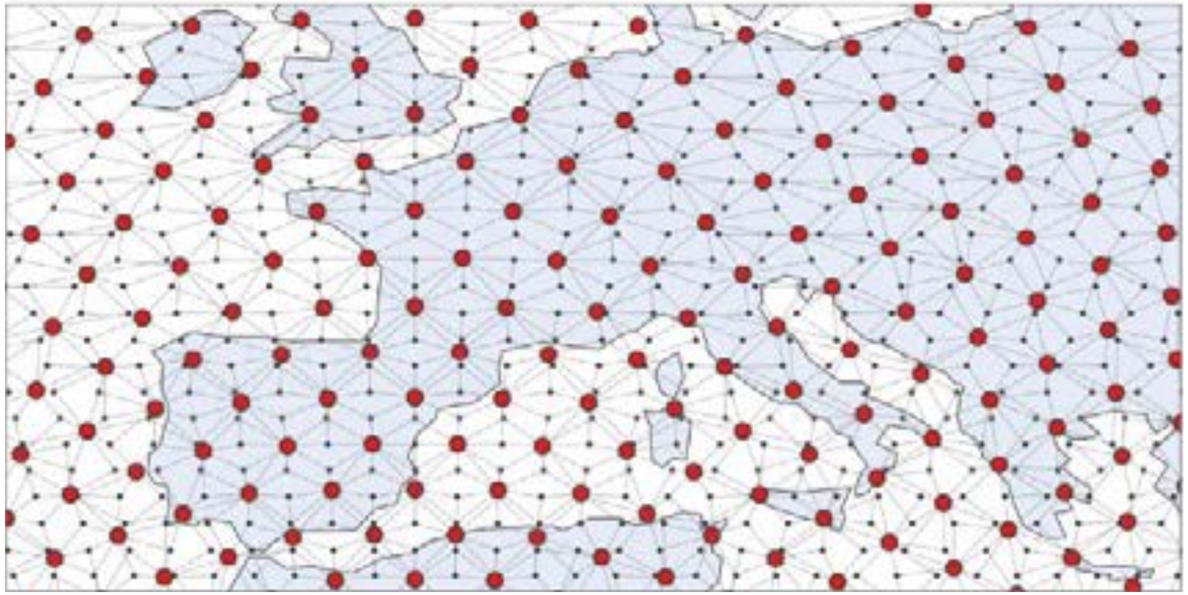
Encoder, GNN



ERA5 – n320 grid

~ 540 000 Nodes
~ 1 Million Edges

Decoder, GNN



ERA5 – n320 grid

x16 processors
with skip connections

O96 grid ~ 40 000 Nodes

AIFS – The Processor

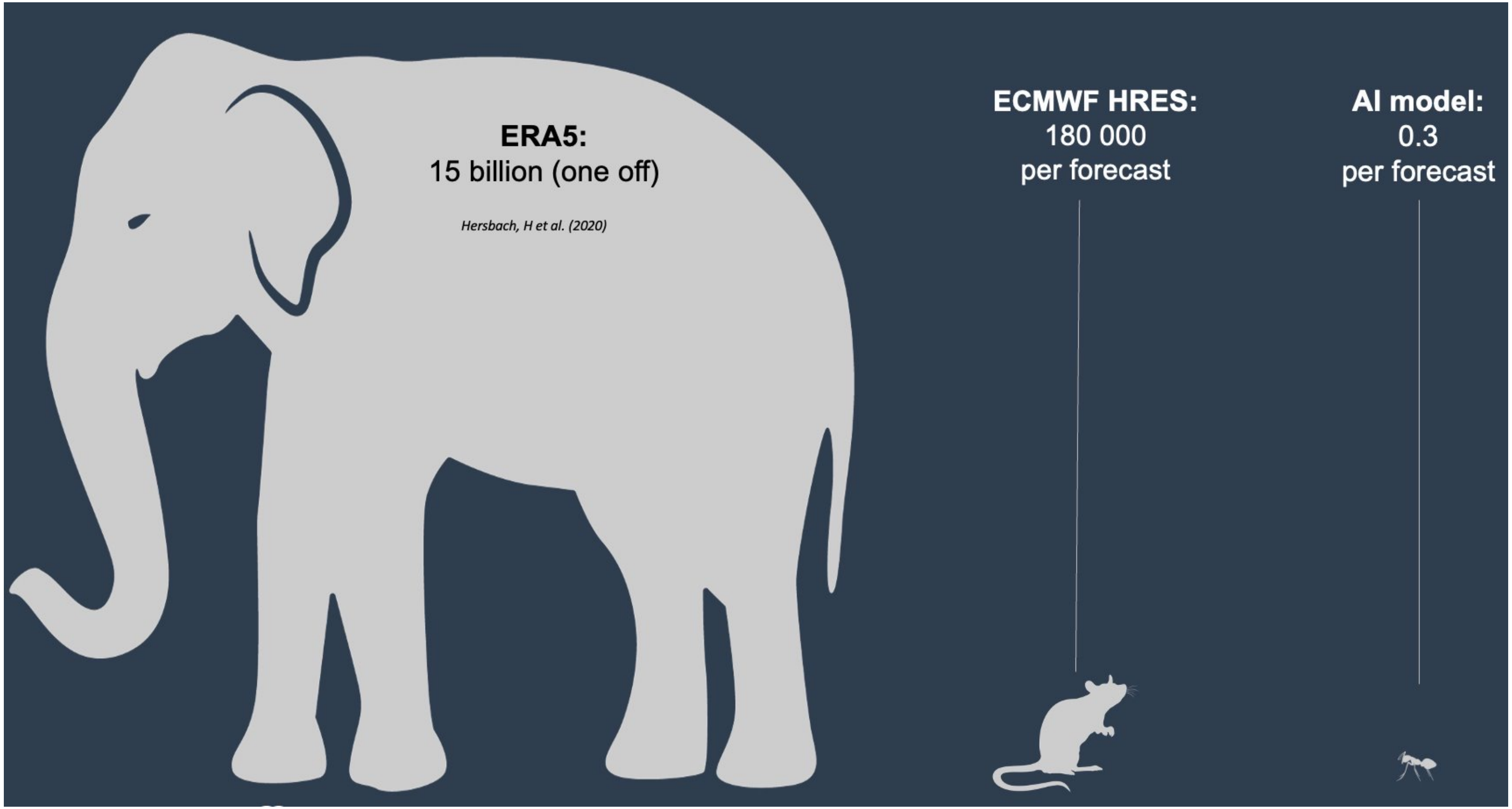
Transformer (like in LLMs) that works with a sliding attention window

Orange point: Target node
Blue points: Nodes that the target nodes attend in one processor layer
Gray points: How far information can travel within multiple processor layers

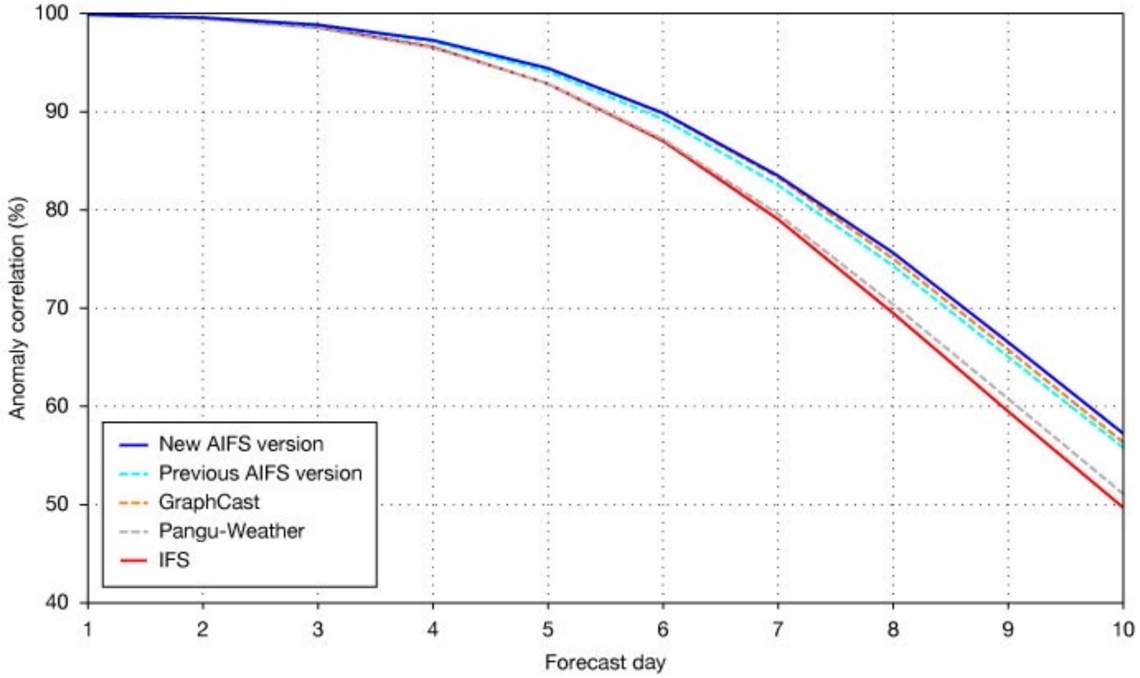
(Here lower resolution than AIFS processor grid for visualization purposes)

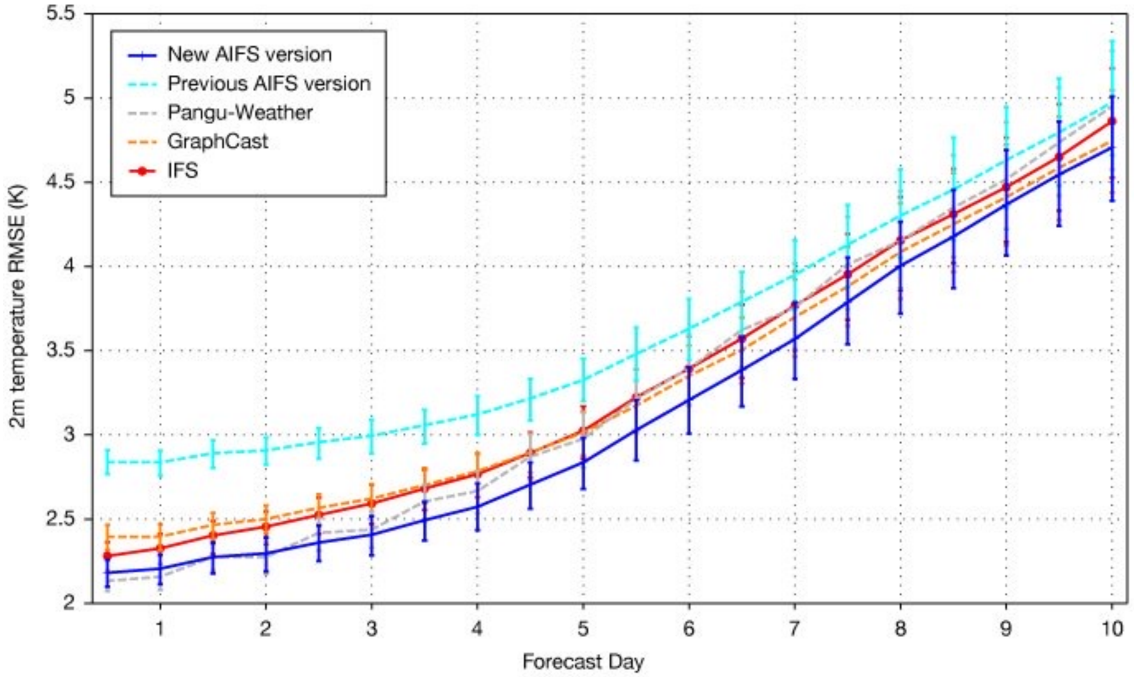
New transformer architecture in use since February 2024:

How costly is AIFS?



AIFS forecast scores in 2022

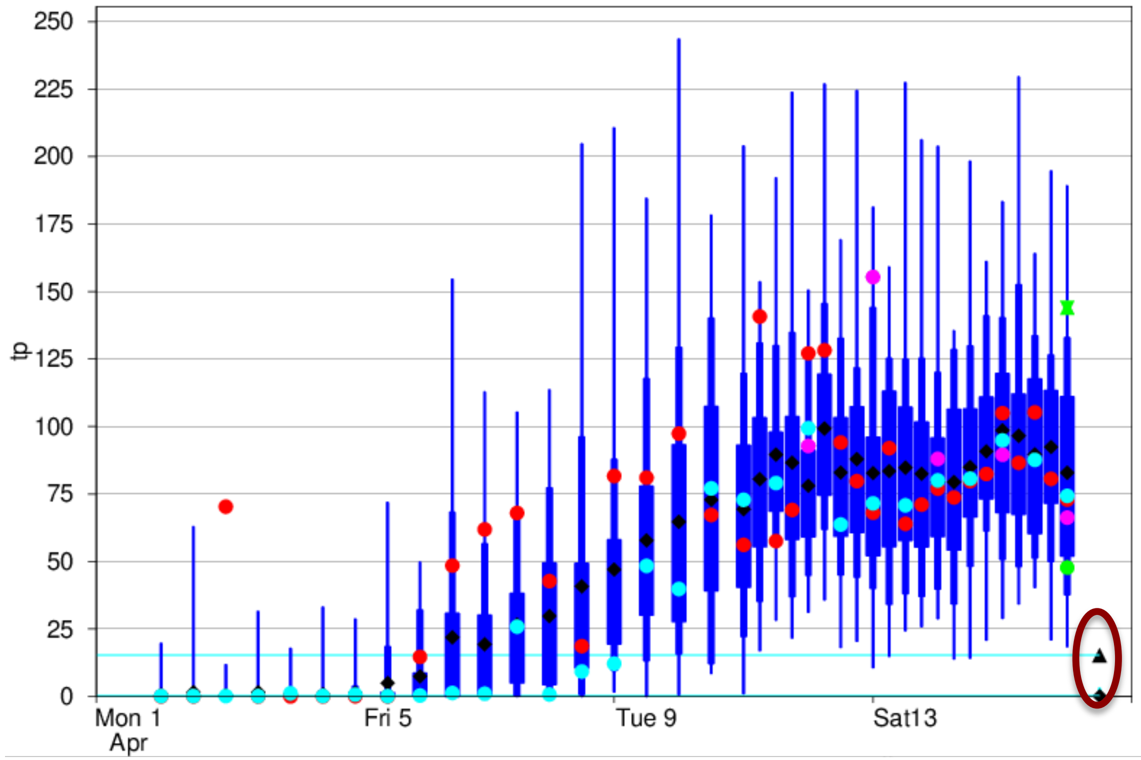




Case Study – Extreme precipitations in the UAE region (16 April 2024)

tions

Total Precipitation



Forecast Initialization

ENS distribution – blue
ENS mean – black diamond
ENS control – red dot

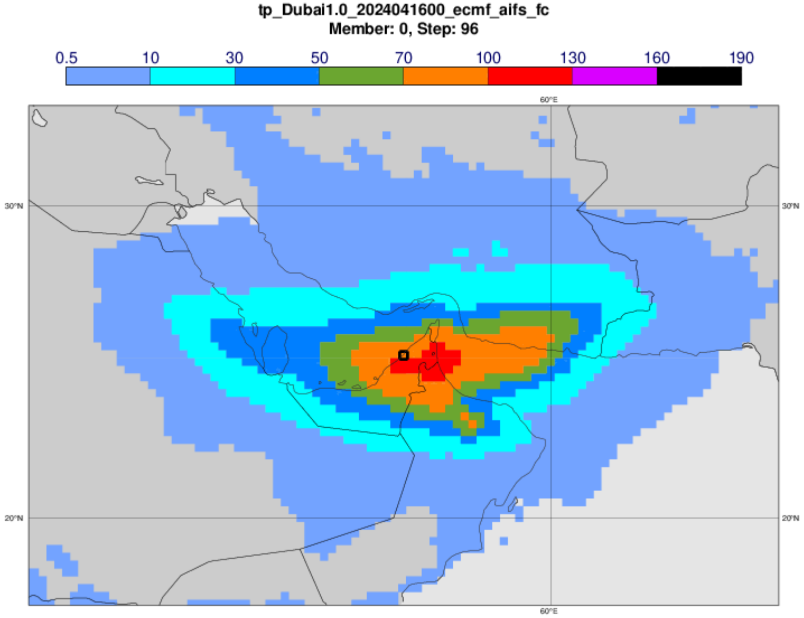
AIFS – cyan dot

M-climate distribution - cyan
M-climate mean - black diamond
M-climate max – black triangle

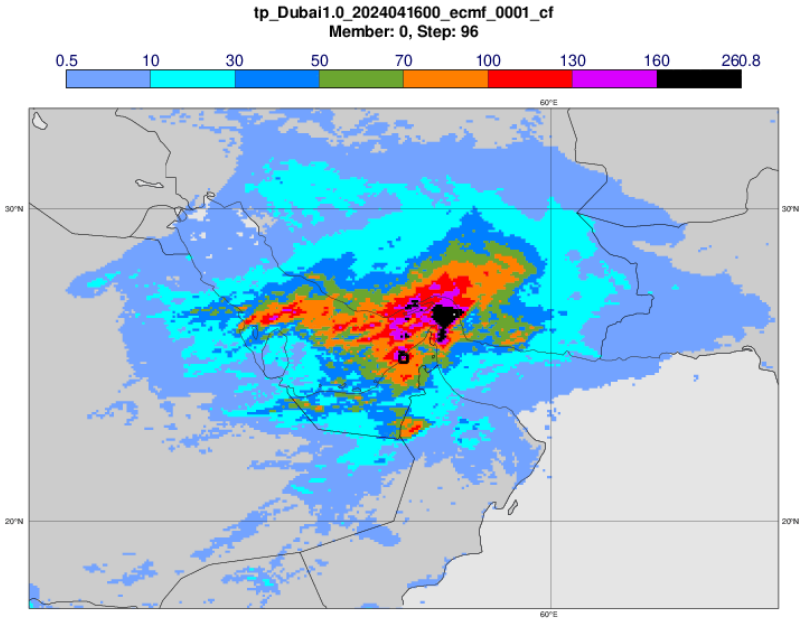
Observation - star

Day 3 forecast

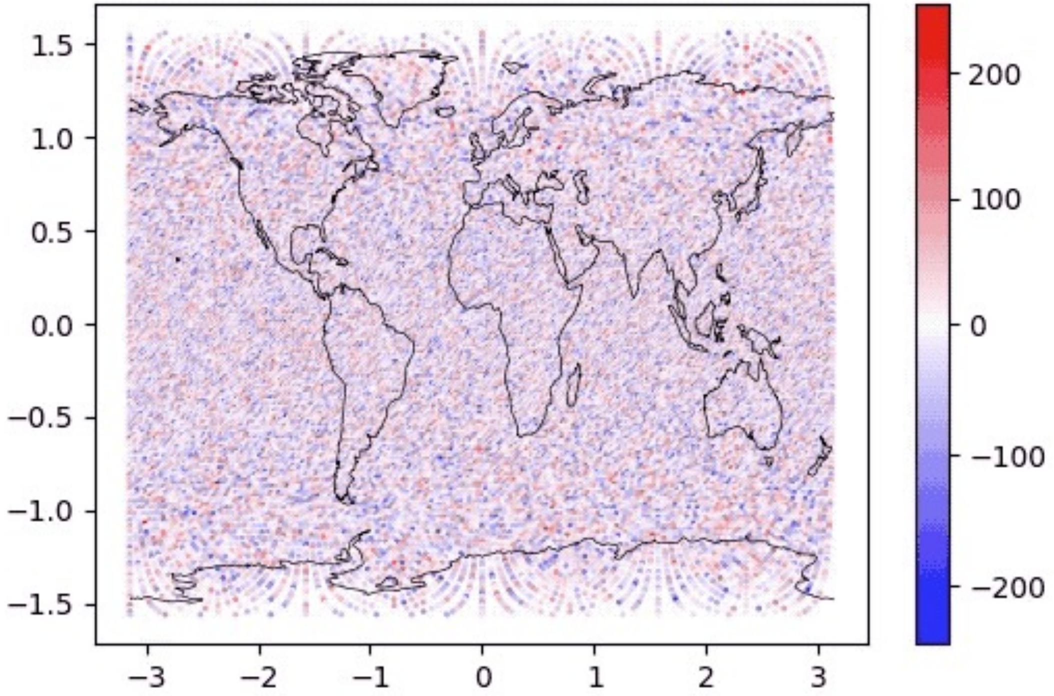
AI



NWP



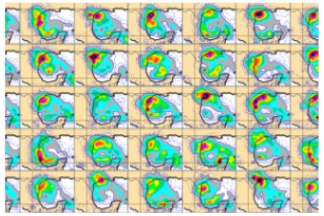
Ensemble forecasting with AIFS



Approach based on *Generative AI* forecast produced as de-noising task

Similar approach as GenCast by Google DeepMind. *Price et al. (2023)*

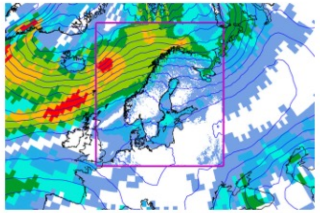
AIFS Blog



Enter the ensembles

21 June 2024

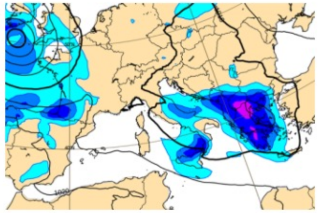
We introduce a first version of an ensemble AIFS, explain how it works, show some early results and explain where you can view charts.



Data-driven regional modelling

23 April 2024

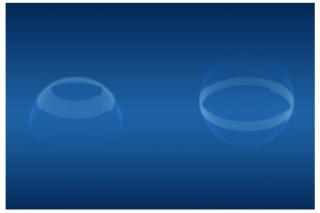
With colleagues from MET Norway, we describe our collaboration on regional modelling and outline Anemoi, our work towards an ML framework for data-driven weather forecasts.



It's rain(ing) data

4 March 2024

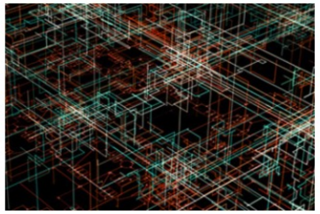
We provide an update on the AIFS, including the addition of precipitation fields and open AIFS data for all.



First update to the AIFS

16 January 2024

We have introduced a new version of the AIFS that now runs at a horizontal resolution of 28 km (0.25°) and has an updated architecture. The new model version improves forecast scores, especially for surface variables, where resolution is crucial.



A new ML model in the ECMWF web charts

13 December 2023

With the introduction of a new machine learning (ML) model in our web charts, we discuss the interpretation of scores, the performance/realism dilemma for ML model developers, and how ensemble systems could help in this case.

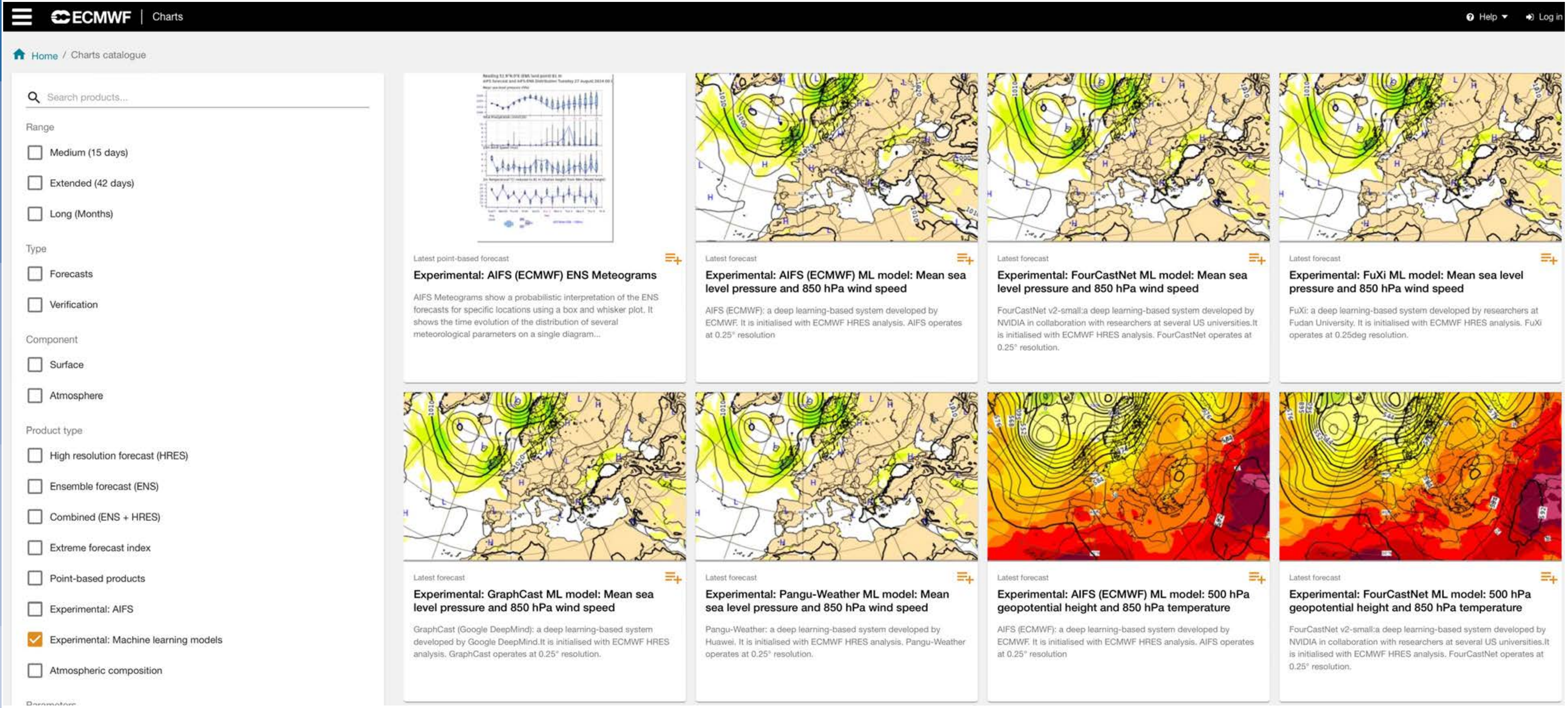
ECMWF unveils alpha version of new ML model

13 October 2023

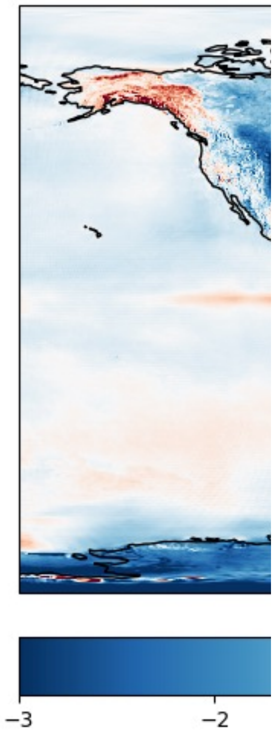
This blog introduces an important companion to the Integrated Forecasting System (IFS), the AIFS, our Artificial Intelligence/Integrated Forecasting System. It is one of three components of our new machine learning project.

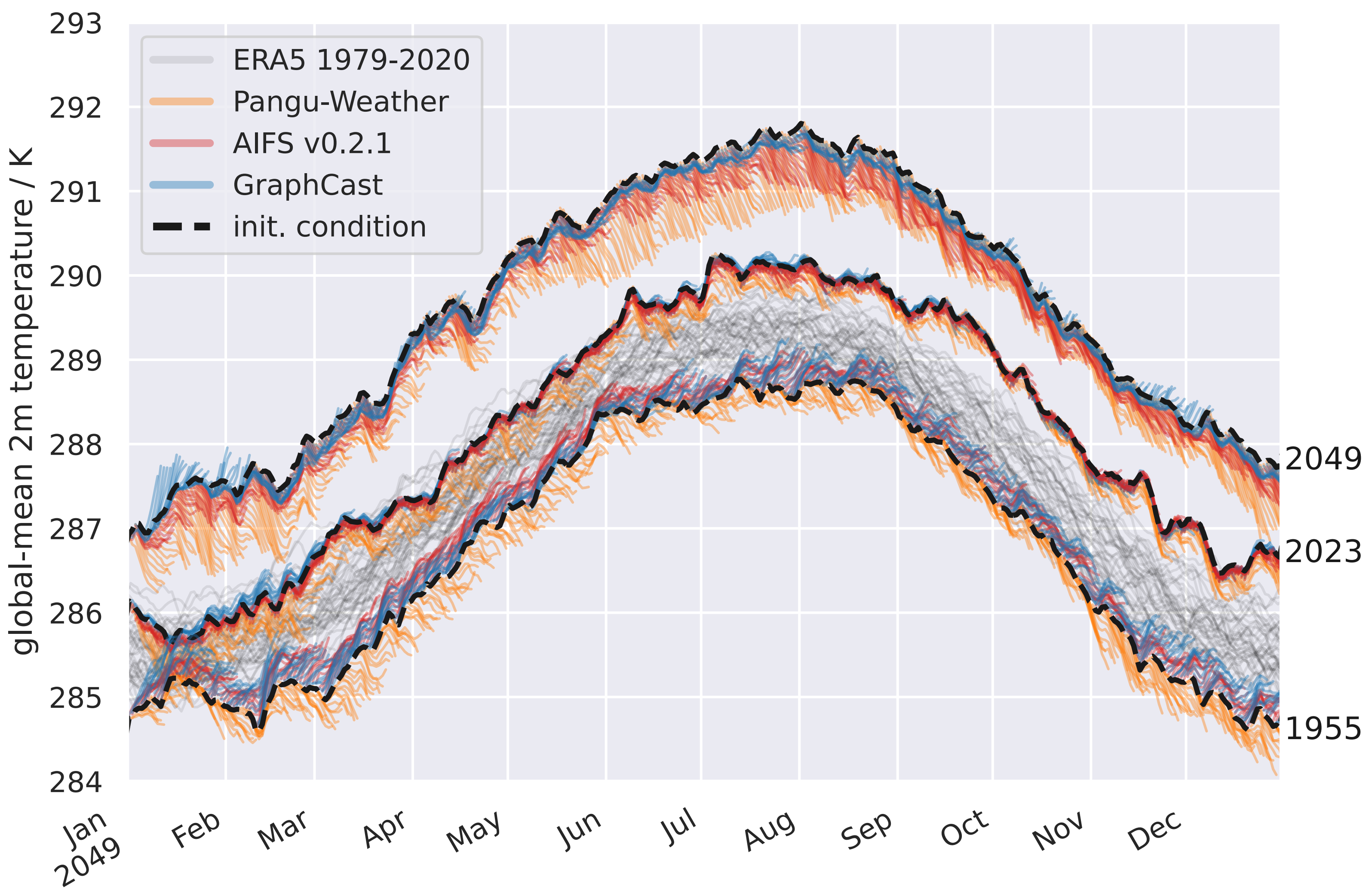
Check out the AIFS blog on the ECMWF website!

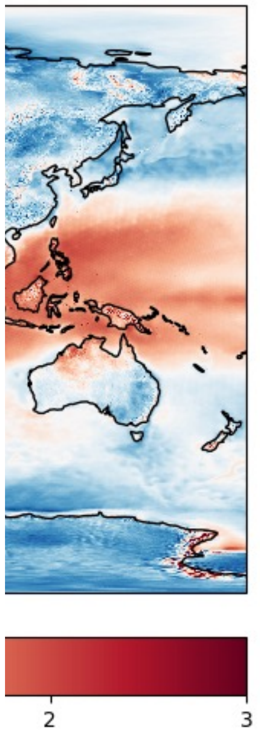
https://www.ecmwf.int/en/about/media-centre/aifs-blog


ECMWF | Charts
Help
Log in
Home / Charts catalogue
Search products...
Range
Medium (15 days)
Extended (42 days)
Long (Months)
Type
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
Atmospheric composition
Latest point-based forecast
Experimental: AIFS (ECMWF) ENS Meteograms
AIFS Meteograms show a probabilistic interpretation of the ENS forecasts for specific locations using a box and whisker plot. It shows the time evolution of the distribution of several meteorological parameters on a single diagram...
Latest forecast
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.
Latest forecast
Experimental: GraphCast ML model: Mean sea level pressure and 850 hPa wind speed
GraphCast (Google DeepMind): a deep learning-based system developed by Google DeepMind.It is initialised with ECMWF HRES analysis. GraphCast operates at 0.25° resolution.
Latest forecast
Experimental: Pangu-Weather ML model: Mean sea level pressure and 850 hPa wind speed
Pangu-Weather: a deep learning-based system developed by Huawei. It is initialised with ECMWF HRES analysis. Pangu-Weather operates at 0.25° resolution.
Latest forecast
Experimental: AIFS (ECMWF) ML model: 500 hPa geopotential height and 850 hPa temperature
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: 500 hPa geopotential height and 850 hPa temperature
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.

ML models beyond the traditional medium-range horizon







Rackow et al. (2024) – in preparation

Funded by
the European Union

Destination Earth

Land Waves

Implemented by ECMWF esa EUMETSAT

Model components
beyond the atmosphere

Wave modelling within AIFS

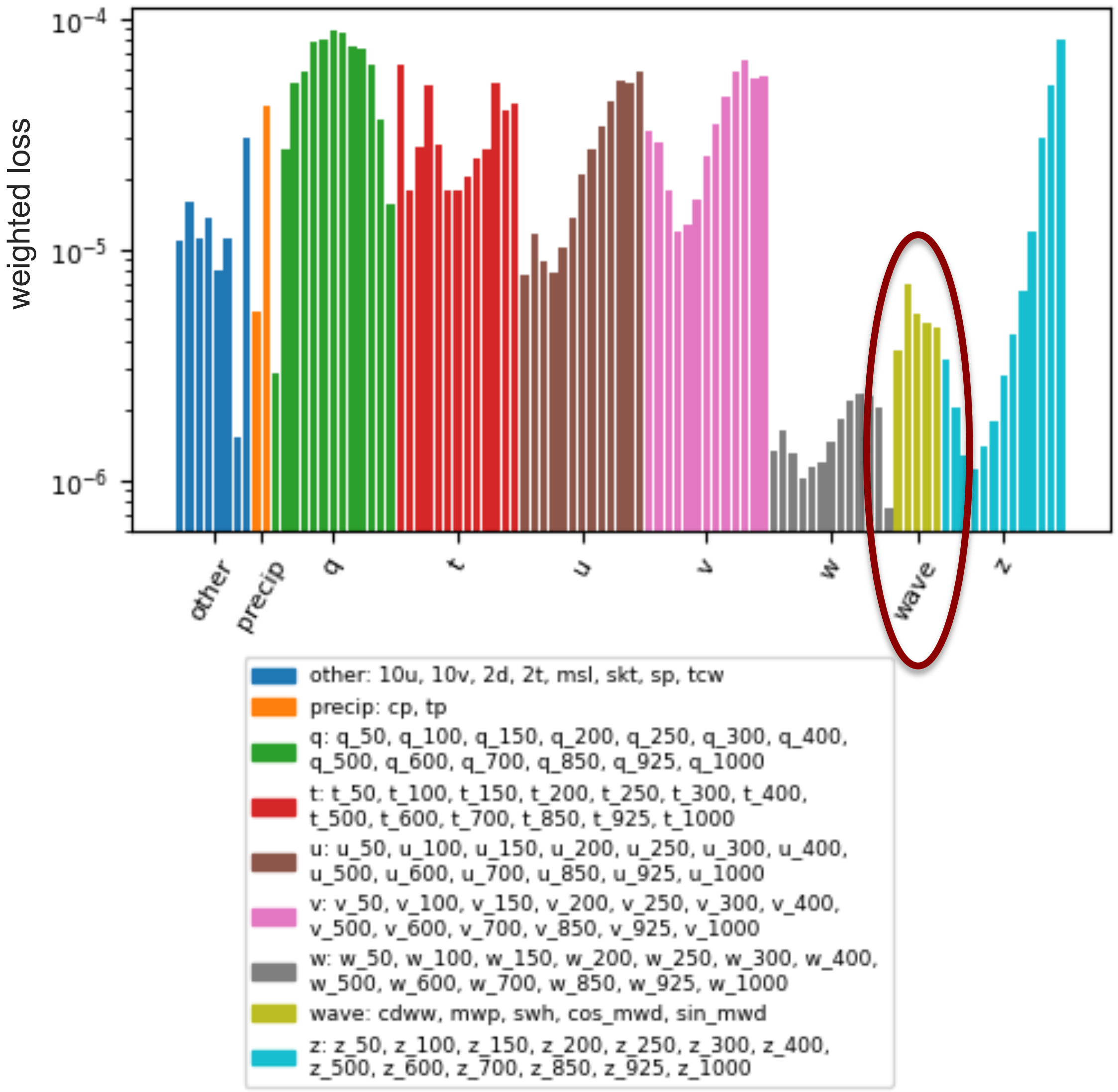
Train AIFS with additional wave variables

Significant wave height
Mean wave direction
Mean wave period
Coefficient of drag with waves

OBJECTIVES:

- Learn the new wave variables together with the atmosphere
- Avoid deteriorating the atmospheric skills
- Test potential benefit from additional wave information

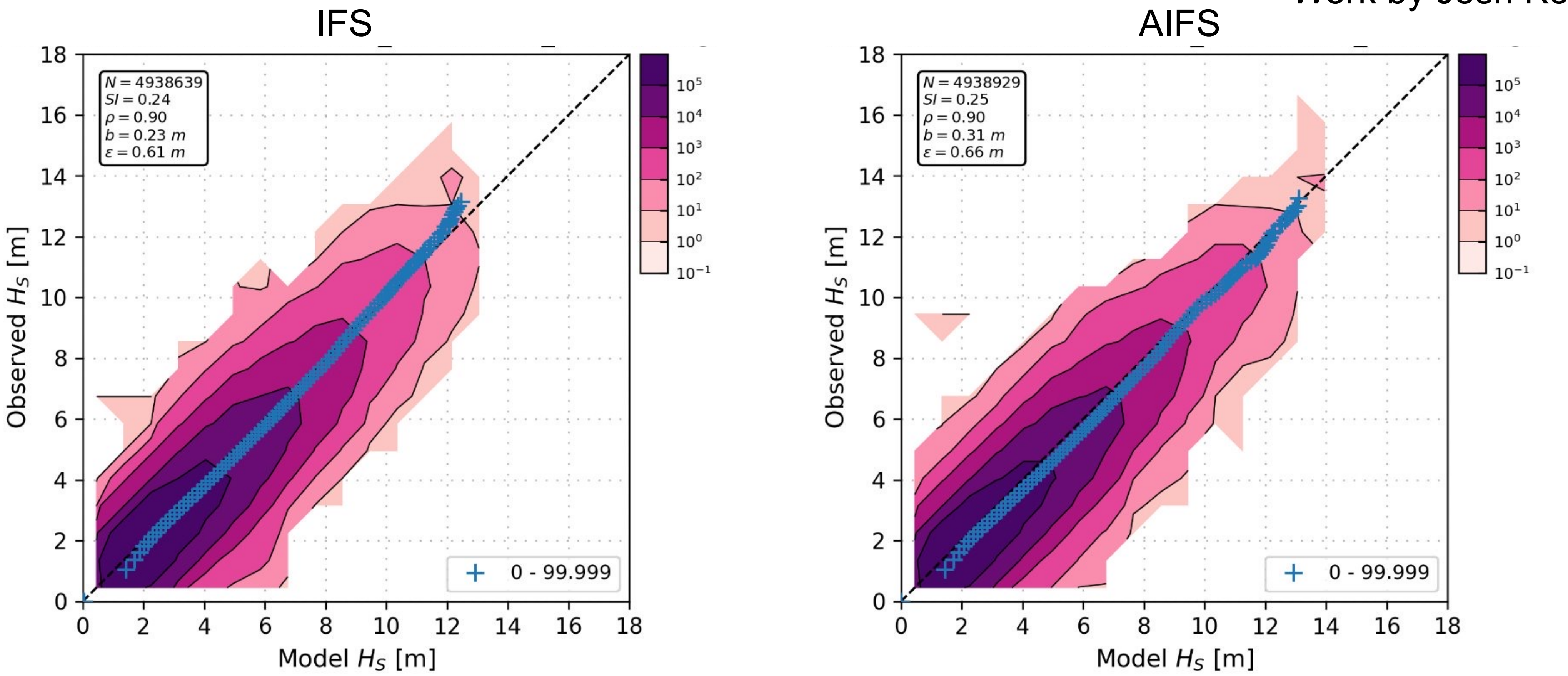
Work by Sara Hahner



Waves performance in AIFS

Comparison to independent altimeter observations for April 2021

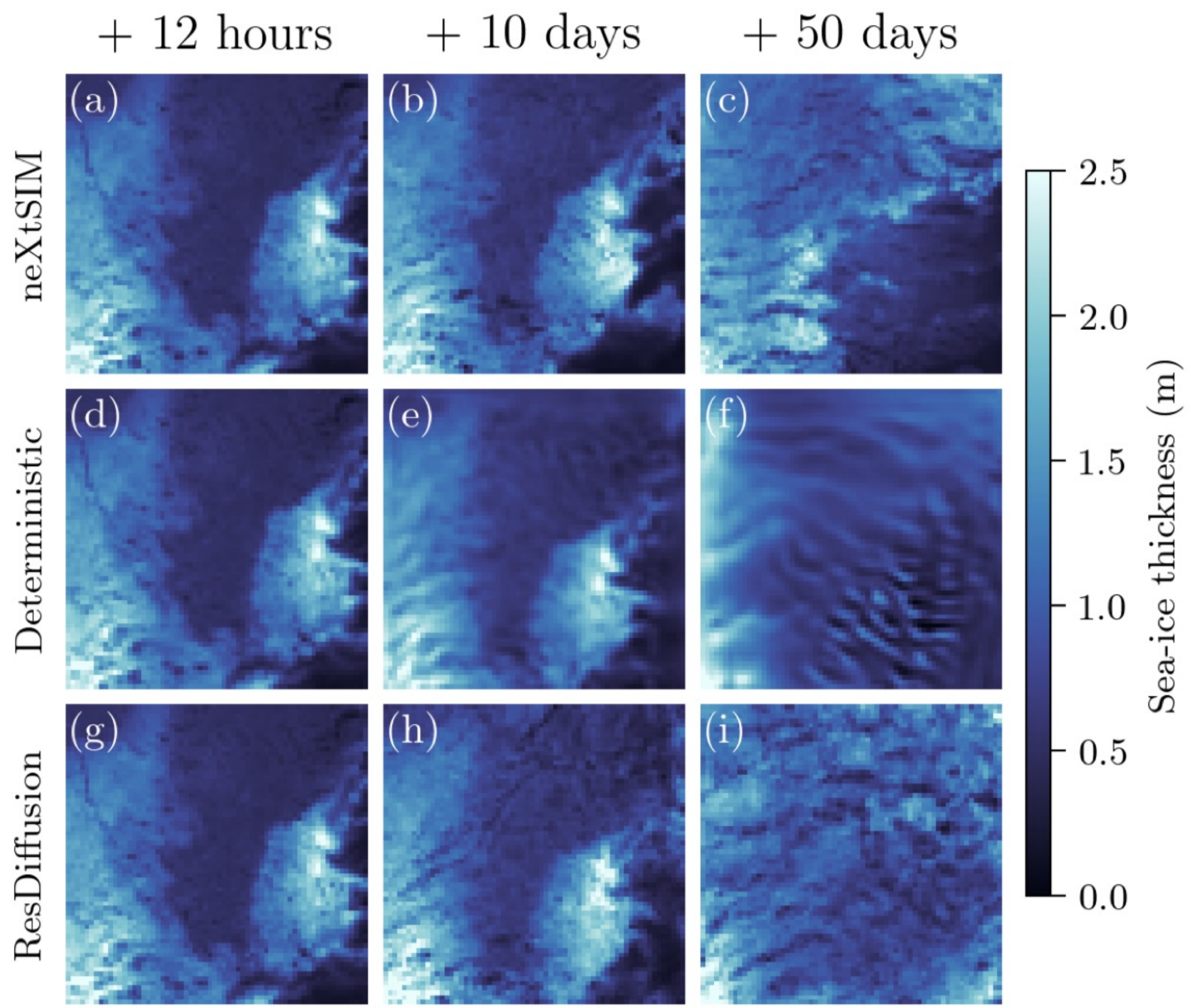
Work by Josh Kousal



AIFS waves are comparable with the operational model, with the caveat of the low resolution

Impact on surface winds is small

Sea ice simulations with generative AI



Finn et al. (2024) – AUTHOREA preprint

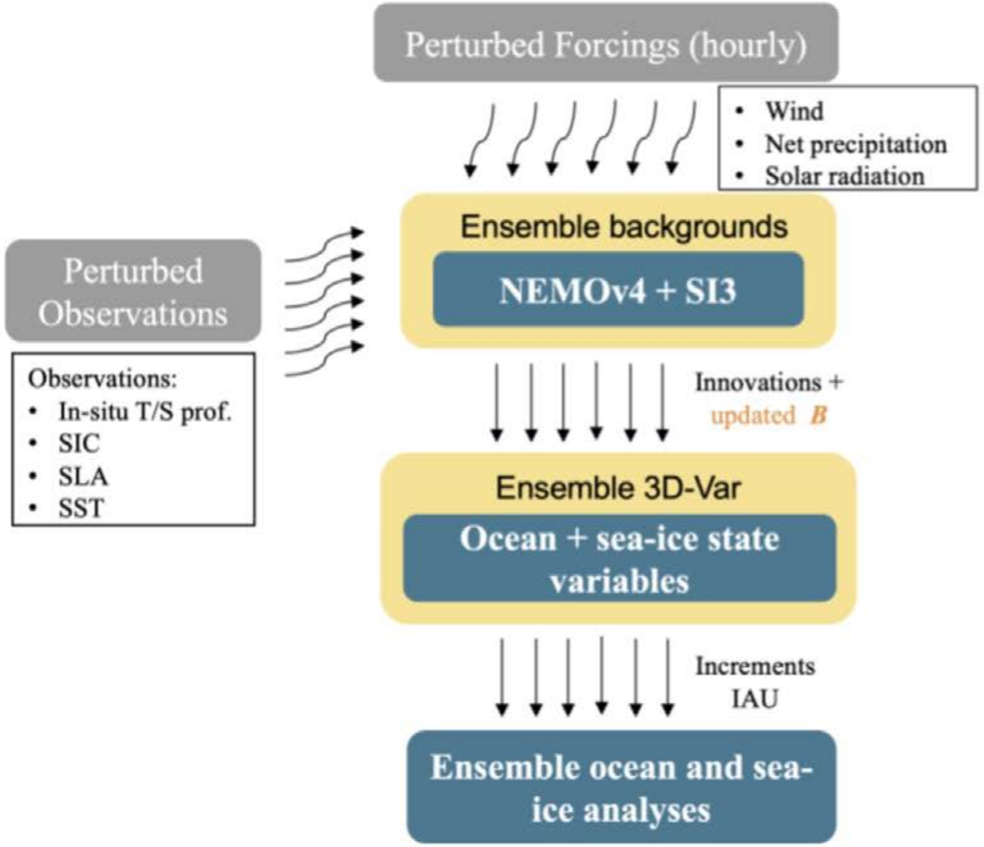
Generative diffusion for regional surrogate models from sea-ice simulations

OPEN QUESTIONS:

- How to normalize sea ice variables?
- What is the optimal ML architecture for sea ice?
- Suitable datasets for training the model?

The first approach will be to use the **ORAS6** reanalysis

ORAS6 – (planned release end 2024)
the 6th Generation of the ECMWF Ocean and Sea ice Reanalysis



	ORAS5	ORAS6
Forcing	ERA-interim: 24 h radiation	ERA5: hourly
Model	NEMOv3.4 + LIM2 0.25-deg	NEMOv4 + SI3 (multi-cat.) 0.25-deg
DA algorithm	Deterministic 3DVar-FGAT	Hybrid Ens 3DVar-FGAT
SST DA	Nudging	Ens 3DVar
Ensemble	4 + 1 control	10 + 1 control
Output	Netcdf	GRIB2
Data cover	1981 onwards	1950 onwards
Production	Sequential	Parallel streams

ORAS6 will be used as oceanic forcing for ERA6

Towards modelling the 3D ocean with ML

CHALLENGES:

- Complex ocean geometries and coastlines.
- Limited resolution and observational constraints of ocean reanalyses.
- Varying timescales – surface velocities change much faster than temperature (Subel and Zanna, 2024)
- The very long dynamic timescales of the deeper ocean.


Rachel Furner


Rilwan Adewoyin


Sarah Hahner

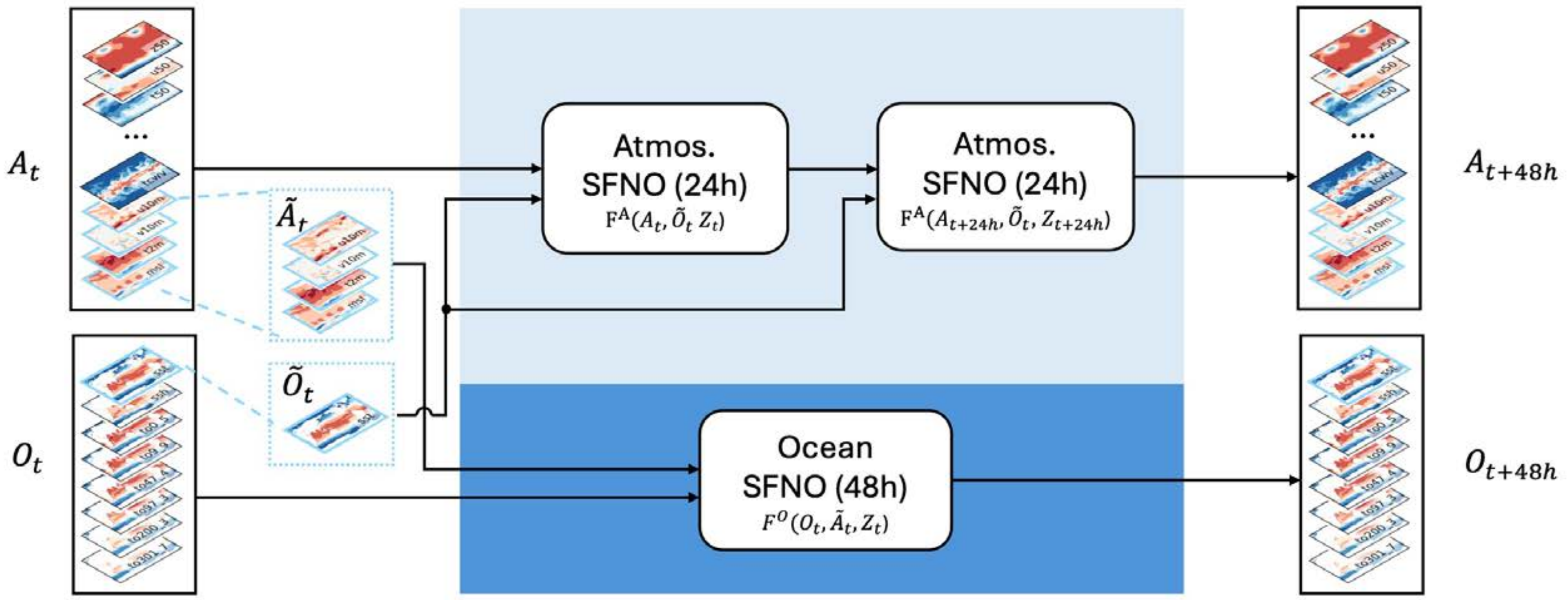

Mario Santa Cruz

APPROACH:

- Customize training and rollout for ocean.
- Design specific graphs for ocean geometry.
- Different depths for different applications. Is an emulator of the full 3d ocean always useful?

Coupling – Still a good strategy for ML?

Design of the Ola ML model by NVIDIA



Coupled Ocean-Atmosphere Dynamics in a Machine Learning Earth System Model

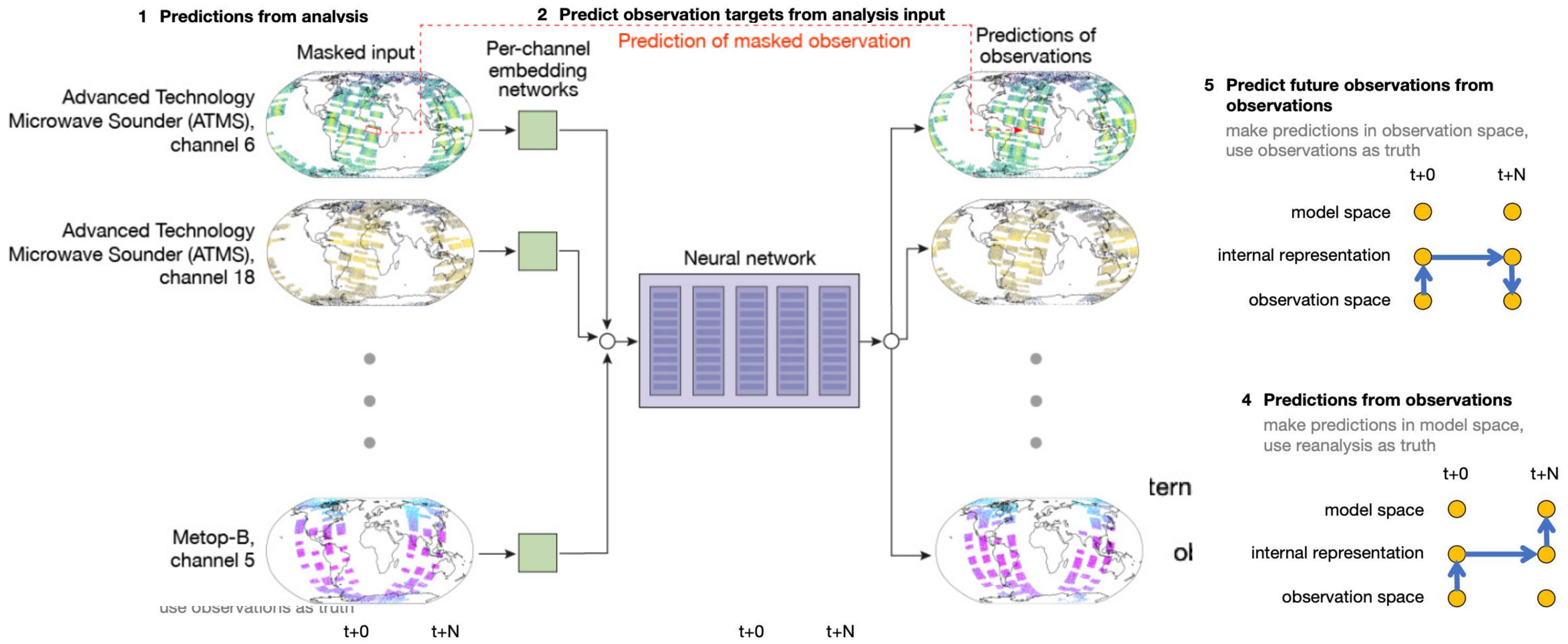
Chenggong Wang *† Princeton University
Michael S. Pritchard * NVIDIA
Noah Brenowitz NVIDIA
Yair Cohen NVIDIA
ev
Thorsten Kurth NVIDIA
Dale Durran University of Washington NVIDIA
Jaideep Pathak * NVIDIA

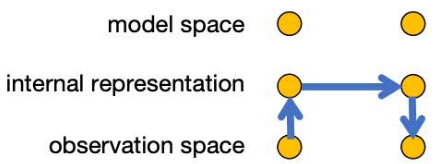
June 14, 2024

Ocean and atmosphere are trained separately by NVIDIA colleagues

What to do in AIFS?

More AI-related activities at ECMWF





EARTH SYSTEM SCIENCE

Red sky at night... producing weather forecasts directly from observations

Tony McNally, Christian Lessig, Peter Lean, Matthew Chantry, Mihai Alexe, Simon Lang

AnemoI an open-source framework for developing machine learning weather forecasting models

AnemoI comprises of components or packages for

- Preparing training datasets
- Conducting ML model training
- Building graphs
- Registry for datasets and trained models
- Operational inference
- Interfacing to verification software

https://github.com/ecmwf

Anemoi packages

- anemoi-utils
- anemoi-datasets
- anemoi-models
- anemoi-graphs
- anemoi-training
- anemoi-inference
- anemoi-registry

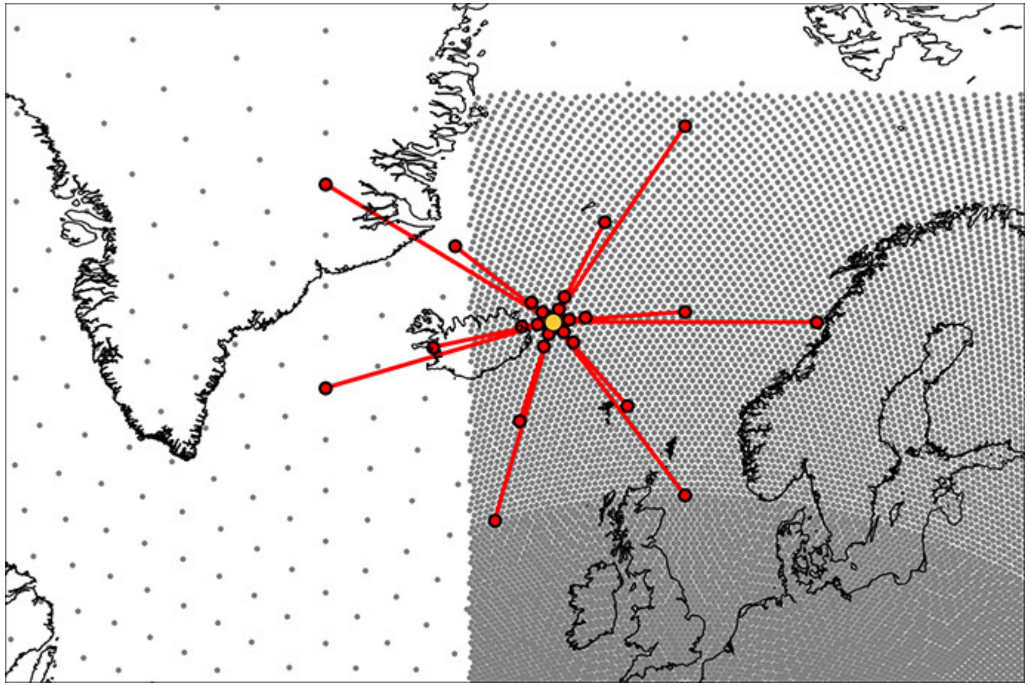
License

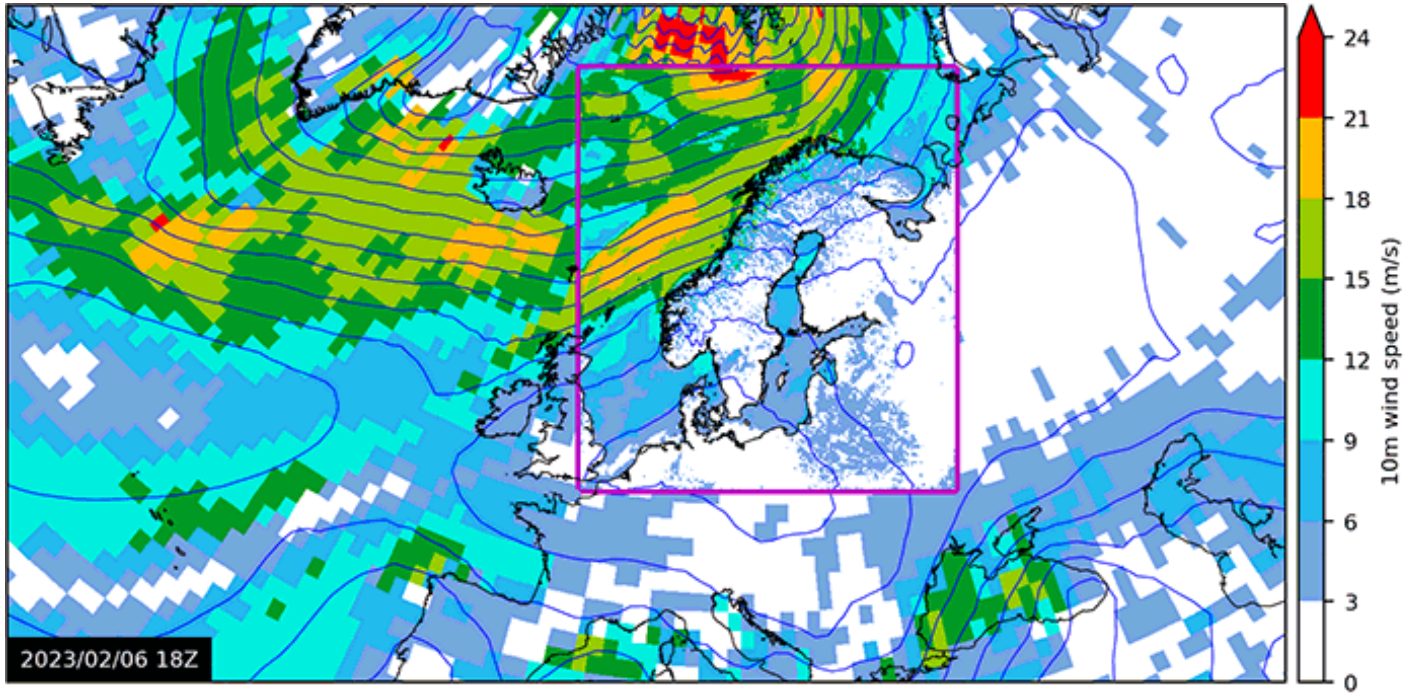
Anemoi is available under the open source Apache License.

AnemoI

an open-source framework for developing machine learning weather forecasting models

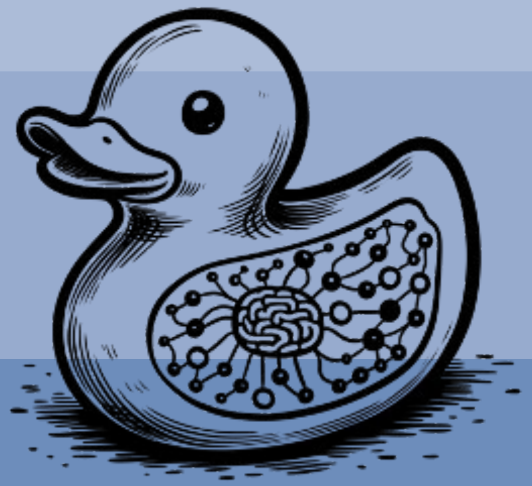
Regional modelling at MetNorway with Anemoi





arXiv preprint: *Regional data-driven weather modeling with a global stretched-grid* by Nipen et al. 2024

Thank you for your time!



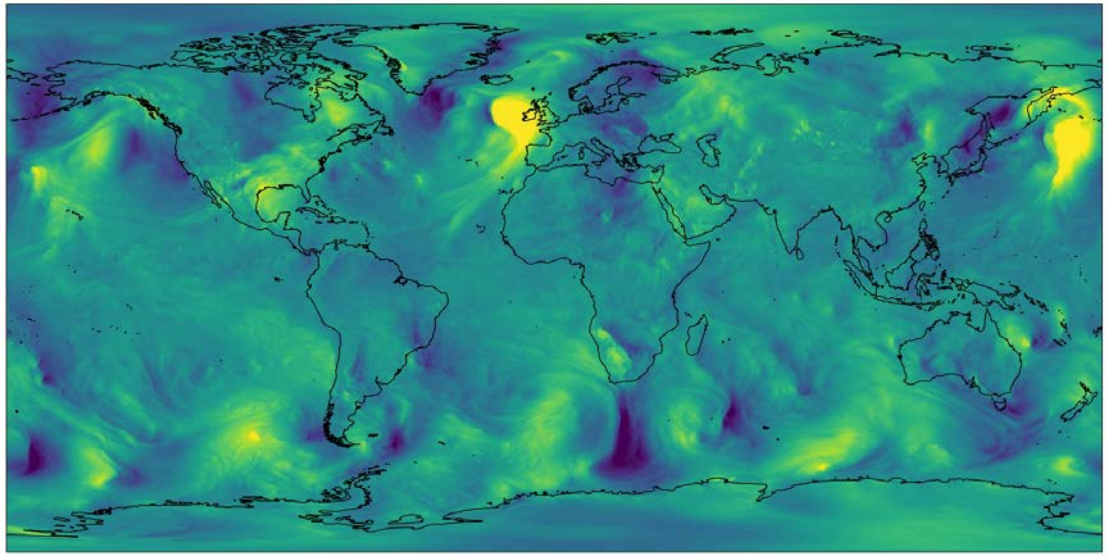
Lorenzo Zampieri

Ocean Modelling Team, Earth System Modelling, Research Dept.
lorenzo.zampieri@ecmwf.int

Funded by the European Union Destination Earth

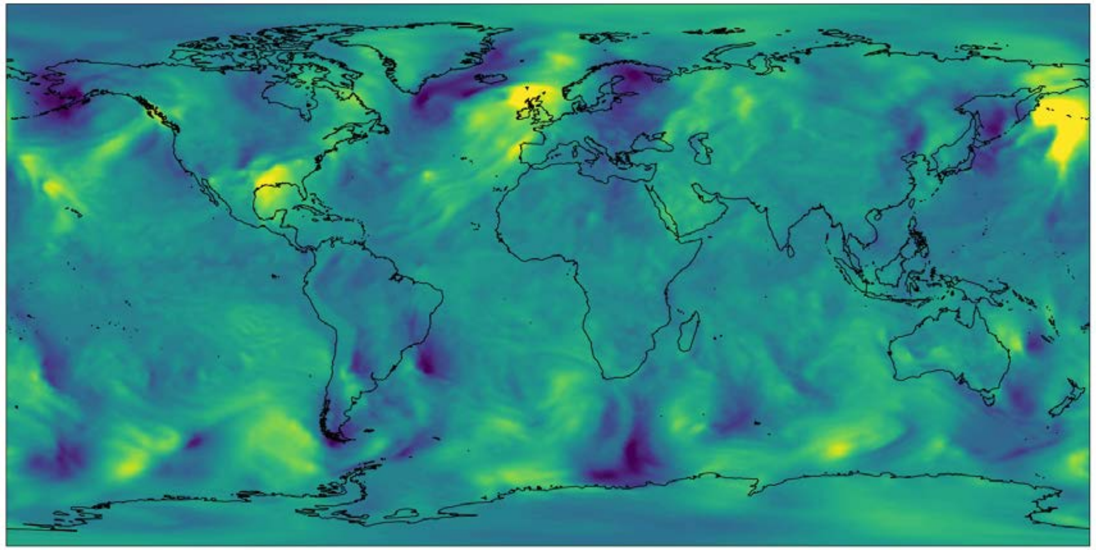
Forecast smoothing – Deterministic vs. Generative

Deterministic AIFS



Forecast Day 10 – Resolution ~ 0.25°

Generative AIFS



Forecast Day 10 – Resolution ~ 1°
Single ensemble member