



University of
Reading

"Do AI models produce better weather forecasts than physics-based models? A quantitative evaluation case study of Storm Ciarán"

Andrew Charlton-Perez, Helen F. Dacre, Simon Driscoll, Suzanne L. Gray, Ben Harvey, Natalie J. Harvey, Kieran M. R. Hunt, Robert W. Lee, Ranjini Swaminathan, Remy Vandaele, Ambrogio Volonté

ECMWF Workshop. 11th September 2024.

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Outline

- Super Brief 'History' – AI Forecasting
- ML models
- Storm Ciaran and Damage
- NWP + ML performance of Storm Ciaran (track, intensification, wind impacts)
- Dynamical Structure of Storm Ciaran
- Conclusions
- Next steps: Microsoft's Aurora model
- VerAI

Team

Helen F.
Dacre



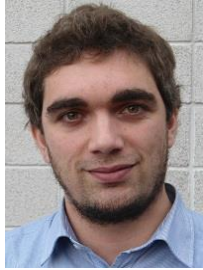
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Driscoll



Suzanne
L. Gray



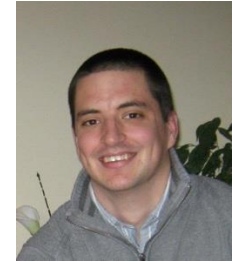
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'History' of ML/AI Forecasting

JOURNAL OF GEOPHYSICAL RESEARCH, VOL. 100, NO. C6, PAGES 11,033–11,045, JUNE 15, 1995

A neural network as a nonlinear transfer function model for retrieving surface wind speeds from the special sensor microwave imager

V. M. Krasnopolsky
General Sciences Corporation, Laurel, Maryland

L. C. Breaker and W. H. Gemmill
National Meteorological Center, Washington, D.C.

Abstract. A single, extended-range neural network (SER NN) has been developed to model the transfer function for special sensor microwave imager (SSM/I) surface wind speed retrievals. Applied to data sets used in previous SSM/I wind speed retrieval studies, this algorithm yields a bias of 0.05 m/s and an rms difference of 1.65 m/s, compared to buoy observations. The accuracy of the SER NN for clear (low moisture) and cloudy (higher moisture/light rain) conditions equals the accuracy of NNs trained

- ML and AI refer to similar things: a set of algorithms that can learn from and make predictions on data, with AI also more broadly referring to technologies using these algorithms for robotics, problem-solving and so on.
- ML/AI has been present in climate research for quite some time. (Krasnopolsky)
- First forecasting attempt: 2018 by scientists at the European Centre for Medium Range Weather Forecasts (ECMWF). Dueben and Bauer (2018)

Geosci. Model Dev., 11, 3999–4009, 2018
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Challenges and design choices for global weather and climate models based on machine learning

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Received: 16 June 2018 – Discussion started: 28 June 2018

Revised: 30 August 2018 – Accepted: 12 September 2018 – Published: 1 October 2018

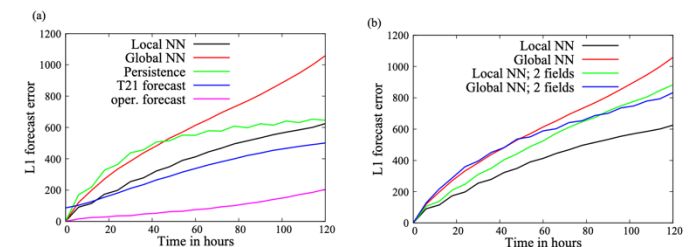


Figure 3. (a) Globally integrated absolute forecast error for the best local network (9×9 stencil), the global network, a persistence forecast, an IFS forecast at TL21 resolution and the operational weather forecast of ECMWF. The persistence forecast shows a 12-hourly fluctuation since Z500 has a weak 12-hourly cycle in the tropics due to atmospheric tides. (b) The same globally integrated absolute forecast error for the best local and global network as in (a) plus the best results for local and global networks that use 2mT as additional prognostic field.

'History' of ML/AI Forecasting

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New Approach to Calculation of Atmospheric Model Physics: Accurate and Fast Neural Network Emulation of Longwave Radiation in a Climate Model

Vladimir M. Krasnopolsky, Michael S. Fox-Rabinovitz, and Dmitry V. Chalikov

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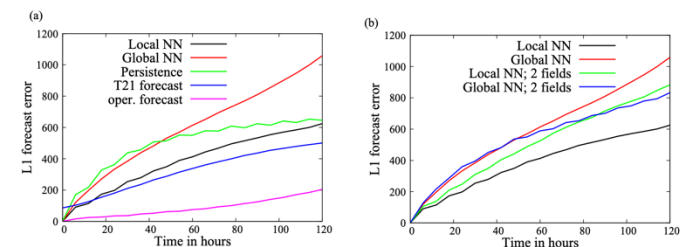


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Artificial Neural Systems

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Vladimir M.
 Dmitry V. Cl

Using Ensemble of Neural Networks to Learn Stochastic Convection Parameterizations for Climate and Numerical Weather Prediction Models from Data Simulated by a Cloud Resolving Model

Vladimir M. Krasnopolsky ✉, Michael S. Fox-Rabinovitz, Alexei A. Belochitski

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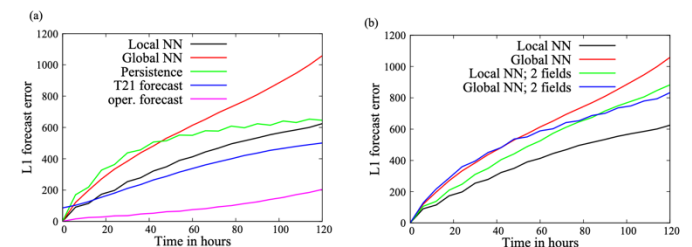


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Using Ensemble of Neural Networks for Convection Parameterization in Weather Prediction Resolving Model

Advances in Artificial Neural
 Research Article | Open Access
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 First published: 07 May 2013 | h
 Academic Editor: Ozgur Kisi

A neural network technique to improve computational efficiency of numerical oceanic models ☆

Vladimir M. Krasnopolsky ¹ ✉, Dmitriy V. Chalikov ², Hendrik L. Tolman ¹ ✉

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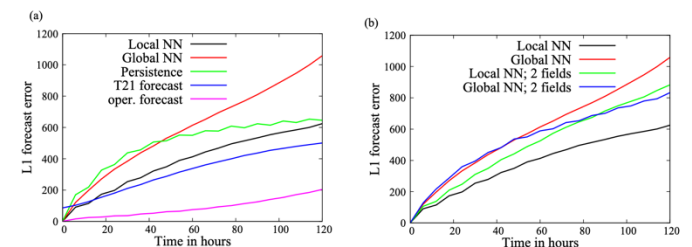


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'History' of AI Forecasting

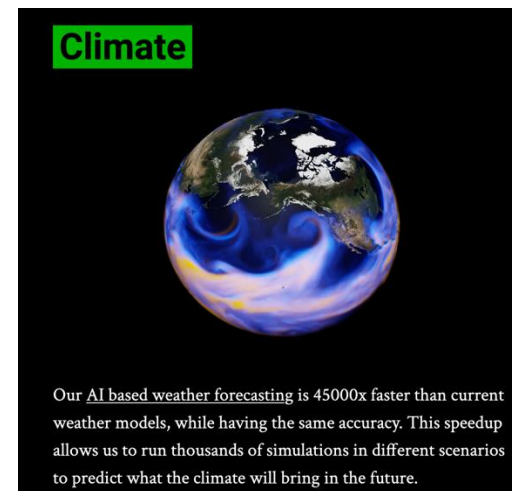
How AI models are transforming weather forecasting: a showcase of data-driven systems

6 September 2023

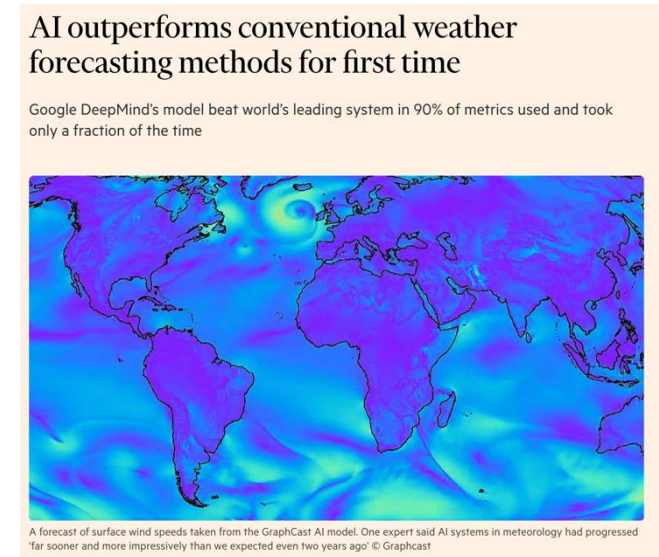


• Image: ECMWF

- First forecasting attempt: 2018 by scientists at the European Centre for Medium Range Weather Forecasts (ECMWF). Dueben and Bauer (2018)
- In 2022/23 enter the tech giants (Huawei, NVIDIA, Google).
- The creation of ML/AI weather forecasting models that can rival and sometimes outperform traditional NWP.
- Advancements in ML techniques, use of GPUs, alongside the publication of a Weatherbench dataset, a 10-year roadmap for ML by the ECMWF, and other developments, have changed the landscape dramatically in recent years.
- Benefits, accuracy, computational cost, ensembles, **45000x faster than current NWP.**



• Image: Anima Anandkumar



• Image: FT

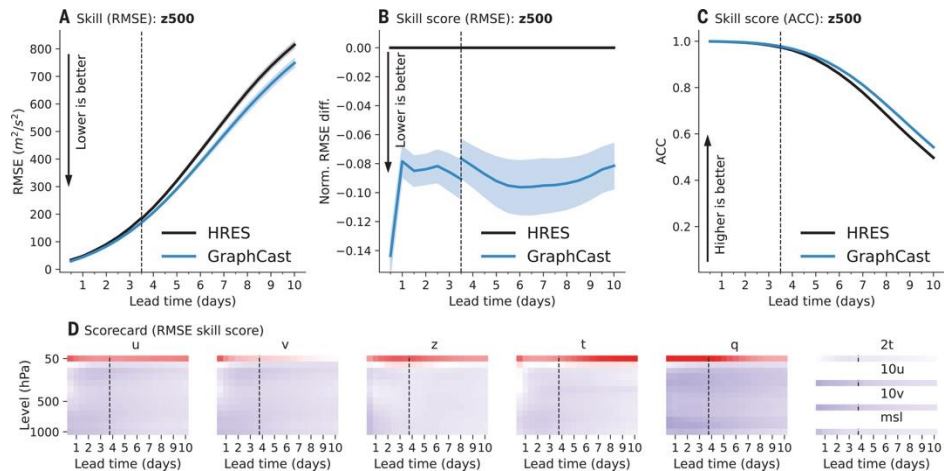
'History' of AI Forecasting

- Rapid progress in weather forecasting has occurred in the last two years.

EMERGING TECHNOLOGIES

AI can now outperform conventional weather forecasting – in under a minute, too

Dec 14, 2023



From Lam et al. (2023)

ARTIFICIAL INTELLIGENCE

Weather forecasting is having an AI moment

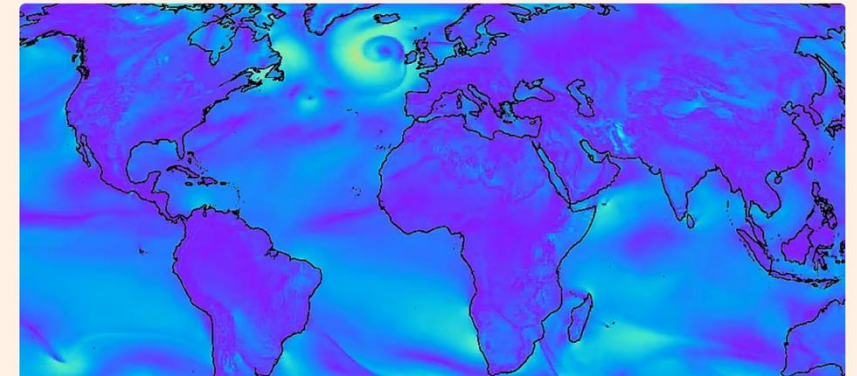
AI-text detection tools are really easy to fool.

Missa Heikkilä
Dec 14, 2023

Climate science [+ Add to myFT](#)

AI outperforms conventional weather forecasting methods for first time

Google DeepMind's model beat world's leading system in 90% of metrics used and took only a fraction of the time



ML models

- **All four models come from the 'tech giants':**
 - **FourCastNet** (NVIDIA - implements a vision transformer architecture with an Adaptive Fourier Neural Operator - AFNO).
 - **FourCastNet v2** (NVIDIA – uses Spherical Fourier Neural Operators SFNOs)
 - **Pangu-Weather** (Huawei - Transformer based architecture)
 - **GraphCast** (Google - Graph Neural Networks)

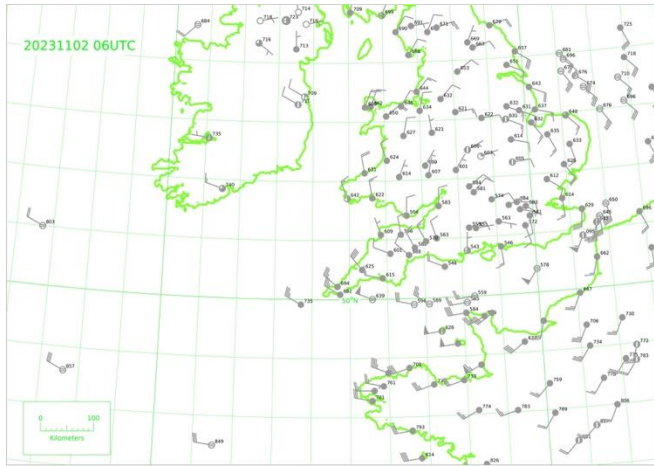
All models train on ECMWF data.

Models are showing considerable ability: equal or better than NWP in many domains. Their ability to forecast extremes is more open, and the focus of analysis has been different.

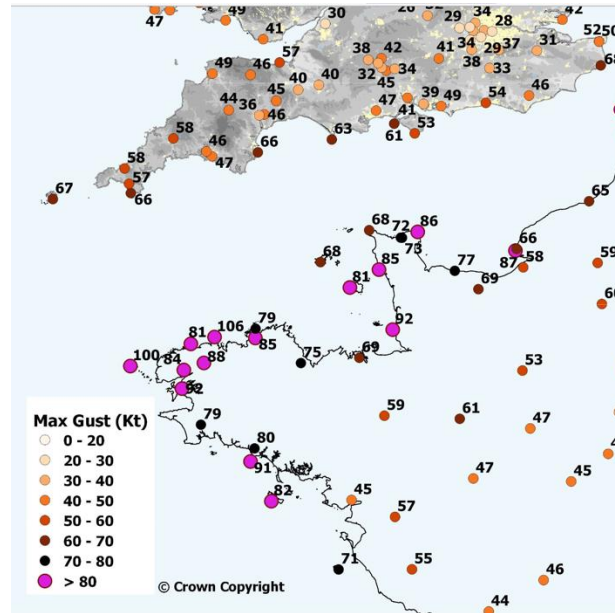
Storm Ciarán

Storm Ciarán evolved from a weak disturbance to a **deep storm** in November 2023.

- First seen as a low-pressure weather system south of Newfoundland at about 00 UTC on 31 October 2023.
- Tracked quickly across the Atlantic before undergoing explosive deepening.



Surface land and ship station
SYNOP observations of Storm
Ciarán at 06 UTC 2 November 2023
extracted from the MetDB database



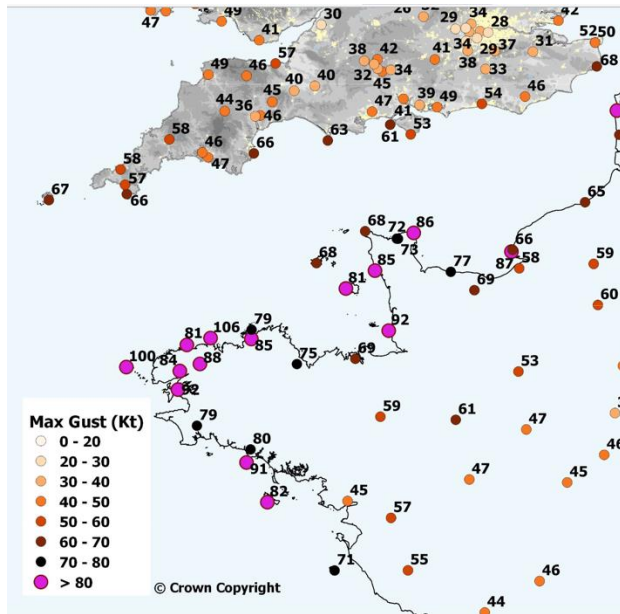
Max wind gust speed 1-2 November 2023

https://www.metoffice.gov.uk/binaries/content/assets/metofficegovuk/pdf/weather/learn-about/uk-past-events/interesting/2023/2023_09_storm_ciaran_1.pdf

Storm Ciarán - A Record Breaking Storm

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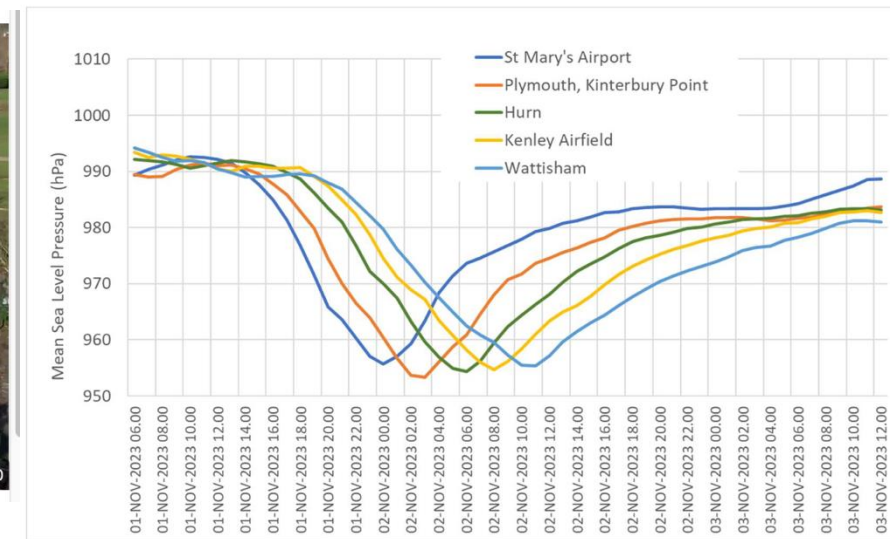


Max wind gust speed 1-2 November 2023

https://www.metoffice.gov.uk/binaries/content/assets/metofficegovuk/pdf/weather/learn-about/uk-past-events/interesting/2023/2023_09_storm_ciaran_1.pdf



Jersey tornado - 'strongest in almost 70 years'



Record low MSLP for November in England


Storm Ciarán - Damage, Disruption

Storm Ciarán caused substantial damage and disruption in the UK and continental Europe.

- Across Northern Europe, at least **16 people were killed**.
- Multiple airports, train services in Europe were shutdown.
- An estimated 1.2 million households in northern France were left without electricity and more than 1 million residents were cut off from the mobile telephone network.

Closer to home:


- Approximately 10,000 homes in Cornwall were left without power, hundreds of schools were closed and many train services were disrupted by fallen trees
- Red weather warning issued by the Jersey Met Office more than a day ahead, closed all Channel Island Schools, airports, harbours and many non-essential businesses on 2 November



Channel Islands Shipping Area Wind Warning
C.I. Warnings cover the area bounded by the French coast between Cap de la Hague and Ile de Brehat, 50 degrees north and 3 degrees west.

Warning Level
Red

Wind Warning 1/11
Issued 08:52 UTC Wednesday 01 November 2023



S to SE severe gale F9 with gusts to 60kt expected soon veering SW to W violent storm F11 with gusts to 85kt later.

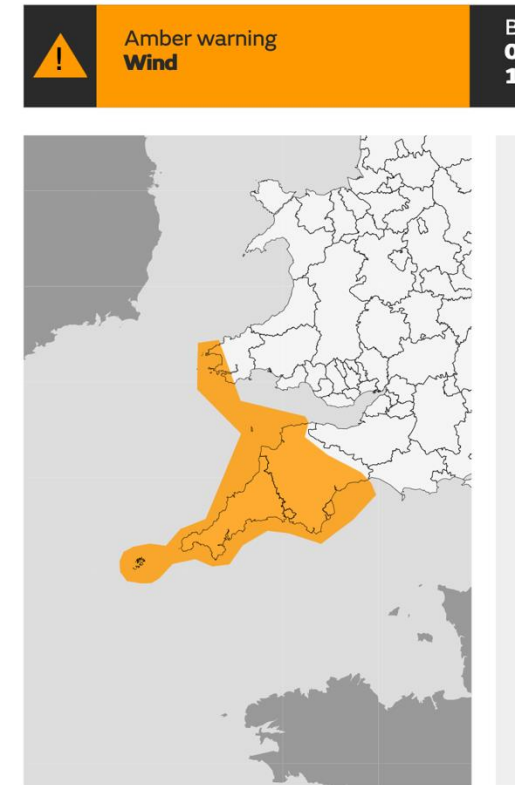
IMMINENT
SOON
LATER

0 to 6 hours from the time of issue.
6 to 12 hours from the time of issue.
More than 12 hours from the time of issue

For the wind forecast specific to Jersey see <https://www.gov.je/weather/>
For the wind forecast specific to Guernsey see <https://www.gov.je/weather/guernsey-forecast>

South Cove at Fort Regent Signal Station

COLOUR	WARNING	ACTION
GREEN	NO WARNING	None
YELLOW	STRONG WIND	Caution with wind sensitive activity. Secure loose objects.
ORANGE	GALE	Remain vigilant. Check the latest forecast.
RED	STORM	Avoid outside activity. Follow advice of authorities.



Do AI models produce better forecasts than physics-based models?

- Not only record breaking, extreme, but at the time it represents a valuable **out-of-sample test** for the ML-models
 - **FourCastNet**
 - **FourCastNet v2**
 - **Pangu-Weather**
 - **GraphCast**

Compared with forecasts from NWP (and reanalysis):

- **ECMWF (including IFS HRES)**
- **Met Office**
- **JMA**
- **NCEP**

Storm Ciarán - Storm Track/MSLP

- First seen as a low-pressure weather system south of Newfoundland at about 00 UTC on 31 October 2023.
- Tracked quickly across the Atlantic before undergoing explosive deepening.
- Initialised forecasts at 00UTC on 31 October
- Track is well forecast by IFS HRES and ML-models
- **BUT** small differences in the low pressure centre location are critical for accurate predictions needed for weather warnings along the south coast of England.

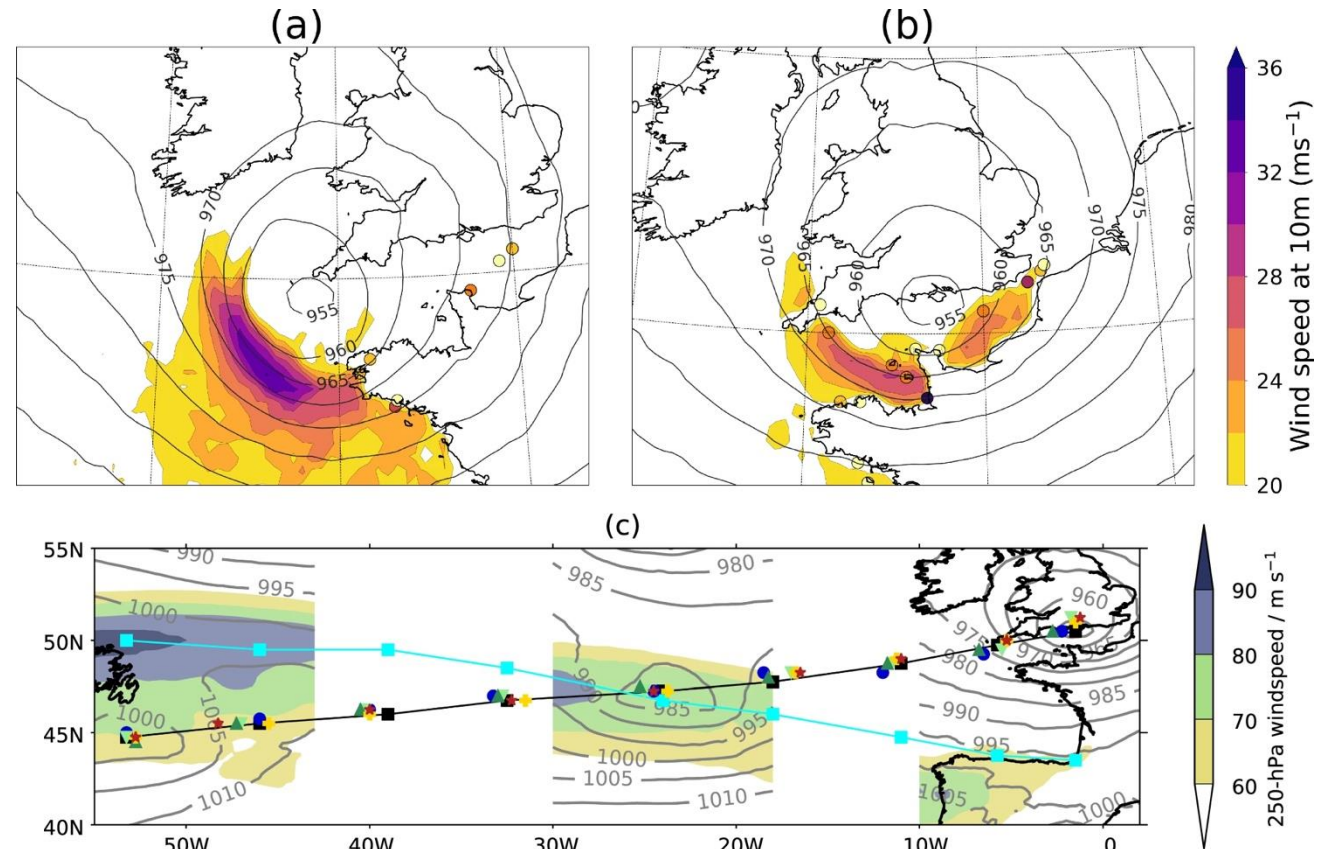
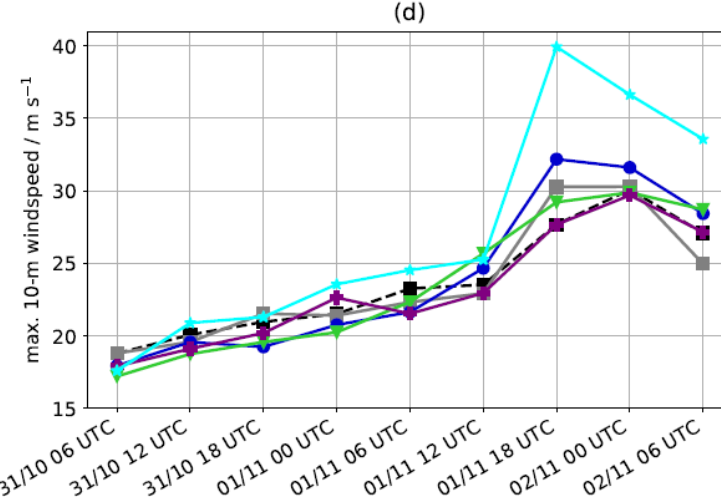
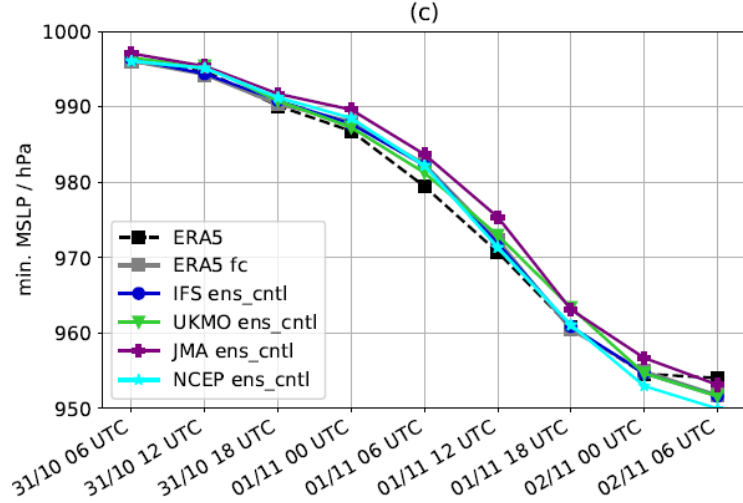
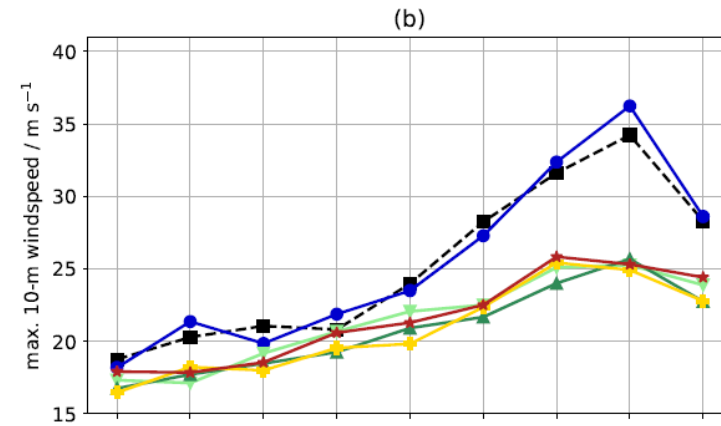
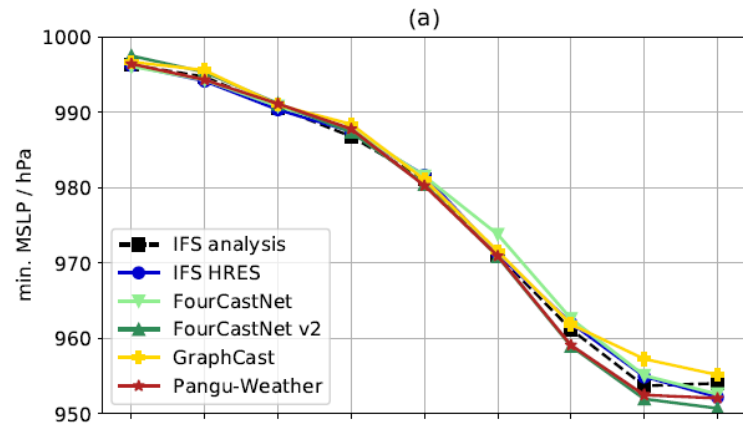


Figure 1: (a, b) Maps of 10-m wind speed (shading) and MSLP (contours) at (a) 00 UTC and (b) 06 UTC 2 November 2023 from the IFS analysis. (c) Six-hourly track points from the IFS analysis and the IFS HRES forecasts and AI models from 06 UTC 31 October to 06 UTC 2 November 2023 (left to right) together with partial MSLP and 250-hPa wind speed from the IFS analysis at 06 UTC on 31 October, 1 November and 2 November (left to right).

Storm Ciarán

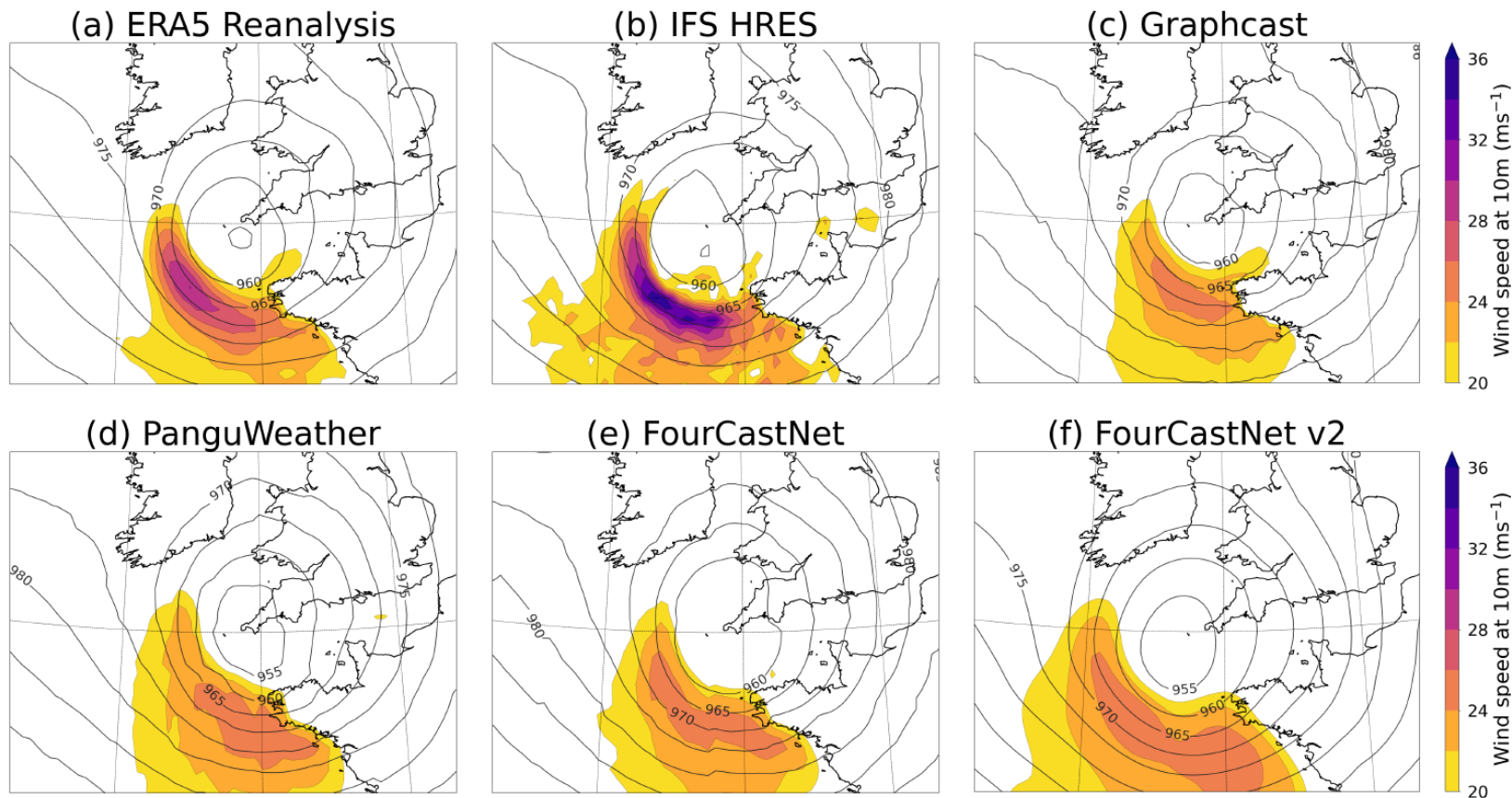
MSLP and max 10m windspeed evolution – ML Models too weak



- All forecasts of minimum MSLP closely follow analysis
- Spread between physical models is similar to the spread between ML-models
- Larger spread in max 10m windspeeds
- The wind speeds forecast by the ML models are far too weak and fail to capture rapid intensification of the winds after about 06 UTC 1 November
- **Note that this isn't the case for ERA-5 analysis forecasts so likely not a "training" problem (or is it?)**

Storm Ciarán

10m winds - 00 UTC 2 November (time of maximum intensity)



- ML models fail to predict the strongest winds in a band following the isobars in the region of the tightest MSLP gradient
- ML models fail to capture the structure and magnitude of the winds in (as seen in the IFS HRES forecast/ERA5/IFS analysis)
- **(*despite ML models being trained on ERA5).**
- **Mixed messages.**

Shifted lead time predictions – Hazard Warnings

- Forecasts are initialised at 00 UTC 1 November, during the onset of Ciarán's rapid intensification phase. They are evaluated 18 hours later and 24 hours later, when Storm Ciarán's peak wind speeds were observed.
- **By shifting the focus to these short lead times from the previous section, the aim is to highlight both the similarities in and differences between, the NWP and ML forecasts on timescales relevant for refining hazard warnings.**

Dynamical structure of Storm Ciarán (18 UTC on 1 November 2023)

- ML models accurately capture the general shape of Storm Ciarán, but struggle to represent frontal structures conducive to mesoscale high-impact features.
- Similarly: maximum wind speeds are weaker in the ML models than in ERA5.

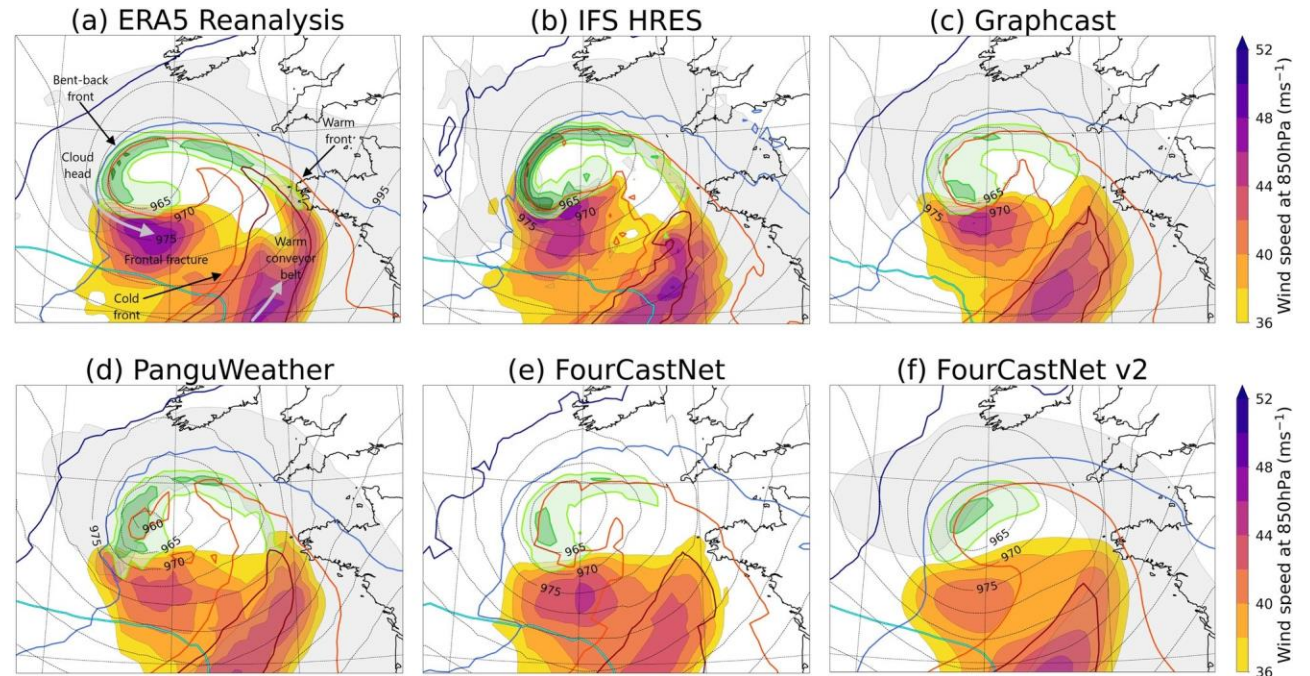
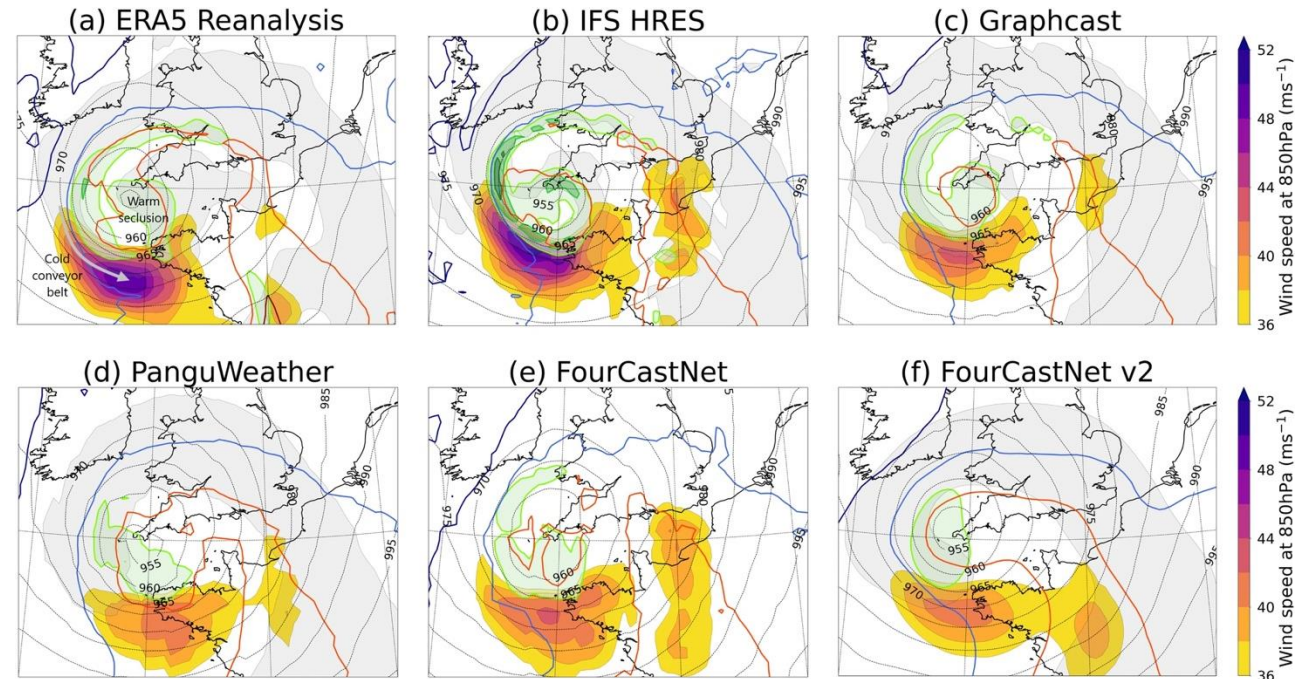


Figure 4: Maps of wind speed at 850 hPa (shading), wind speed at 250 hPa (65 ms^{-1} , cyan contour with high values in the bottom left of the panels), wet-bulb potential temperature at 850 hPa (dark blue, light blue, light red and dark red contours), MSLP (thin grey contours), relative humidity with respect to water at 700 hPa (grey shading encircling regions above 80%), vertical component of relative vorticity at 850 hPa (light-to-dark green shading).

Dynamical structure of Storm Ciarán at 00 UTC on 2 November 2023.

- The structures of the MSLP fields are similar for the different models despite the differences in the wind speed structure and magnitude.
- Wind maxima are consistently underestimated in the ML models when compared to the benchmarks provided by the ERA5 and IFS forecast.



Conclusions



- Forecasts of the rapid MSLP deepening and track of the storms produced by the ML-models were essentially indistinguishable to NWP forecasts. Many important dynamical features of the storm were well captured by the ML models.



- ML-models failed to represent the strength of the cross-front thermal gradient in the bent-back front.
- All four ML models failed to produce the narrow band of very strong winds at the surface that led to the most severe impacts.
- **This is important not least as the economic loss resulting from strong surface winds is often assumed to scale as the cube of normalised wind gust speed over a threshold.**

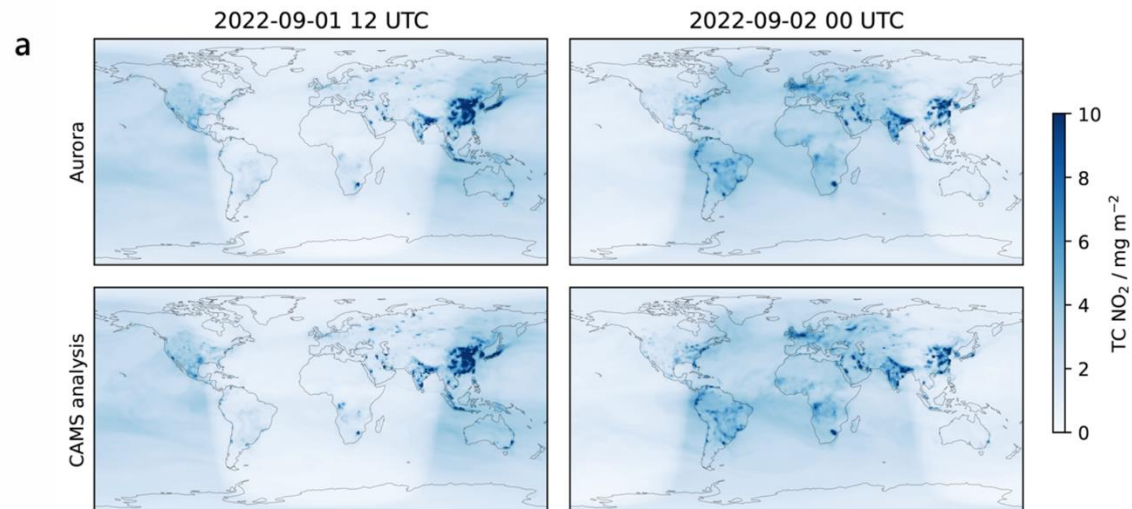


- Ability of ML models to forecast more dynamically unusual storms is an open question.
- **(Starting to explore this now)**
- Physical consistency between models.

Next steps – Aurora Showing the Way?

- "A recent study by Charlton-Perez et al. (2024) underscored the challenges faced by even the most advanced AI weather-prediction models in capturing the rapid intensification and peak wind speeds of Storm Ciarán.
- To help address those challenges, a team of Microsoft researchers developed [Aurora, a cutting-edge AI foundation model that can extract valuable insights from vast amounts of atmospheric data.](#) "

Fast prediction of atmospheric chemistry and air pollution

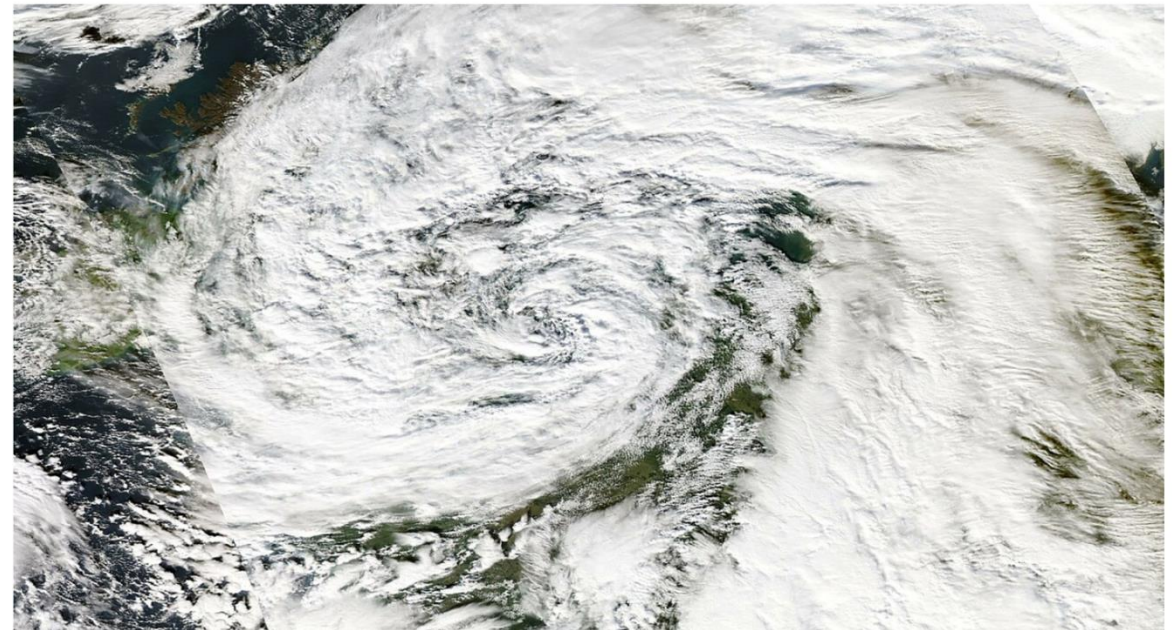


Introducing Aurora: The first large-scale foundation model of the atmosphere

Published June 3, 2024

By [Wessel Bruinsma](#), Senior Researcher; [Megan Stanley](#), Senior Researcher; [Ana Lucic](#), Researcher; [Richard Turner](#), Visiting Researcher; [Paris Perdikaris](#), Principal Research Manager

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Next steps – Aurora Showing the Way?

- "By operating at a high spatial resolution of 0.1° (roughly 11 km at the equator), Aurora captures intricate details of atmospheric processes, providing more accurate operational forecasts than ever before—and at a fraction of the computational cost of traditional numerical weather-prediction systems."

Table 3: Summary of the 10 datasets used to pretrain the different Aurora configurations presented in this work.

Name	Resolution	Timeframe	Pretraining Datasets				Num levels	Size (TB)	Num frames
			Surface Variables	Atmospheric Variables					
ERA5	$0.25^\circ \times 0.25^\circ$	1979-2020	2T, U10, V10, MSL	U, V, T, Q, Z		13	105.43	367,920	
HRES-0.25	$0.25^\circ \times 0.25^\circ$	2016-2020	2T, U10, V10, MSL	U, V, T, Q, Z		13	42.88	149,650	
IFS-ENS-0.25	$0.25^\circ \times 0.25^\circ$	2018-2020	2T, U10, V10, MSL	U, V, T, Q, Z		3	518.41	6,570,000	
GFS Forecast	$0.25^\circ \times 0.25^\circ$	2015-2020	2T, U10, V10, MSL	U, V, T, Q, Z		13	130.39	560,640	
GFS Analysis	$0.25^\circ \times 0.25^\circ$	2015-2020	2T, U10, V10, MSL	U, V, T, Q, Z		13	2.04	8,760	
GIFS Reforecast	$0.25^\circ \times 0.25^\circ$	2000-2019	2T, MSL	U, V, T, Q, Z		3	194.02	2,920,000	
CMCC-CM2-VHR4	$0.25^\circ \times 0.25^\circ$	1950-2014	2T, U10, V10, MSL	U, V, T, Q		7	12.6	94,900	
ECMWF-IFS-HR	$0.45^\circ \times 0.45^\circ$	1950-2014	2T, U10, V10, MSL	U, V, T, Q, Z		7	3.89	94,900	
MERRA-2	$0.625^\circ \times 0.5^\circ$	1980-2020	2T, U10, V10, MSL	U, V, T, Q, Z		13	5.85	125,560	
IFS-ENS-Mean	$0.25^\circ \times 0.25^\circ$	2018-2020	2T, U10, V10, MSL	U, V, T, Q, Z		3	10.37	131,400	
Total							1,219.91	11,023.730	

Table 4: Summary of the datasets used to fine-tune the different Aurora experiments presented in this work.

Name	Resolution	Timeframe	Fine-tuning Datasets				Num levels	Size (TB)	Num frames
			Surface Variables	Atmospheric Variables					
HRES-0.25	$0.25^\circ \times 0.25^\circ$	2016-2021	2T, U10, V10, MSL	U, V, T, Q, Z		13	51.46	179,580	
HRES-0.1	$0.10^\circ \times 0.10^\circ$	2016-2022	2T, U10, V10, MSL	U, V, T, Q, Z		13	18.29	10,220	
CAMSRA	$0.75^\circ \times 0.75^\circ$	2003-2021	2T, U10, V10, MSL,	U, V, T, Q, Z,		13	3.64	55,480	
			TC CO ₂ , TC NO ₂ , TC NO ₂ , TC SO ₂ , TC O ₃ , PM ₁₀ , PM _{2.5} , PM ₁	CO, NO, NO ₂ , SO ₂ , O ₃					
CAMS Analysis	$0.40^\circ \times 0.40^\circ$	Oct 2017-May 2022	2T, U10, V10, MSL,	U, V, T, Q, Z,		13	0.79	3,408	
			TC CO ₂ , TC NO ₂ , TC NO ₂ , TC SO ₂ , TC O ₃ , PM ₁₀ , PM _{2.5} , PM ₁	CO ₂ , NO, NO ₂ , SO ₂ , O ₃					

A flexible 3D foundation model of the atmosphere

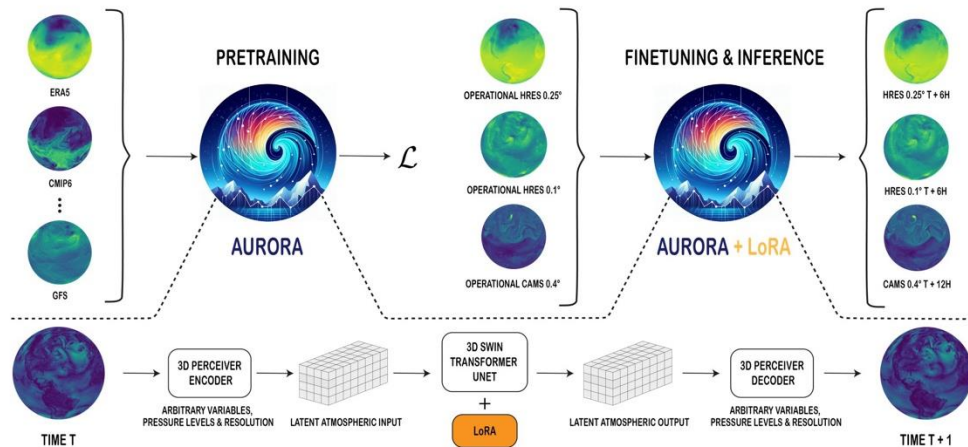
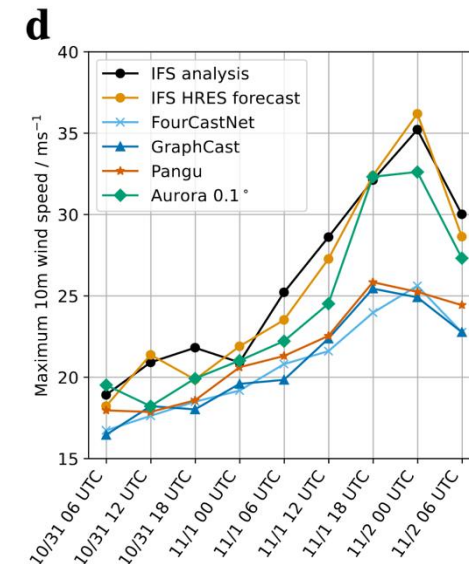


Figure 1: Aurora is a 1.3 billion parameter foundation model for high-resolution forecasting of weather and atmospheric processes. Aurora is a flexible 3D Swin Transformer with 3D Perceiver-based encoders and decoders. At pretraining time, Aurora is optimized to minimize a loss on multiple heterogeneous datasets with different resolutions, variables, and pressure levels. The model is then fine-tuned in two stages: (1) short-lead time fine-tuning of the pretrained weights and (2) long-lead time (rollout) fine-tuning using Low Rank Adaptation (LoRA). The fine-tuned models are then deployed to tackle a diverse collection of operational forecasting scenarios at different resolutions.



VerAI Workshop

- Co-organized by Jochen Brocker and myself.
- Verifying, explaining etc. the AI models.
- Writing up report on this. (can send)

“In a report on extreme weather risks, the House of Commons Public Accounts Committee raised concerns about UK government’s approach in being able to strengthen UK’s resilience to society-wide risks (including extreme weather risks), saying it “lacks the required robust leadership, oversight and urgency”.

... Storm Ciarán was not an unusual storm, and as part of UK preparedness, further work must also go into understanding how much the AI models’ predictions can be trusted for more dynamically unusual storms.”

This is especially important with an increase in the likelihood of extreme weather events as climate change continues.



Digital Construction News

AI forecasting: Storm Ciarán and UK resilience to extreme weather events

May 14, 2024

With the increasing urgency for the UK to strengthen its resilience to extreme weather events, Dr Simon Driscoll and Dr Natalie Harvey from the University of Reading looks at the AI forecasting revolution and the mixed ability of this approach to capture a record-breaking windstorm

Thank you for listening!

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Do AI models produce better weather forecasts than physics-based models? A quantitative evaluation case study of Storm Ciarán

[Andrew J. Charlton-Perez](#) , [Helen F. Dacre](#), [Simon Driscoll](#), [Suzanne L. Gray](#), [Ben Harvey](#), [Natalie J. Harvey](#), [Kieran M. R. Hunt](#), [Robert W. Lee](#), [Ranjini Swaminathan](#), [Remy Vandaele](#) & [Ambrogio Volonté](#)

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Abstract

There has been huge recent interest in the potential of making operational weather forecasts using machine learning techniques. As they become a part of the weather forecasting toolbox, there is a pressing need to understand how well current machine learning models can simulate high-impact weather events. We compare short to medium-range forecasts of Storm Ciarán, a European windstorm that caused sixteen deaths and extensive damage in

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