How new developments in science and AI are helping the EU with better weather forecasts

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ECMWF | EUROPEAN CENTRE FOR MEDIUM-RANGE WEATHER FORECASTS

The strength of a common goal

MAELSTROM

WeatherGenerator

esiwace CENTRE OF EXCELLENCE IN SIMULATION OF WEATHER AND CLIMATE IN EUROPE

Funded by the European Union

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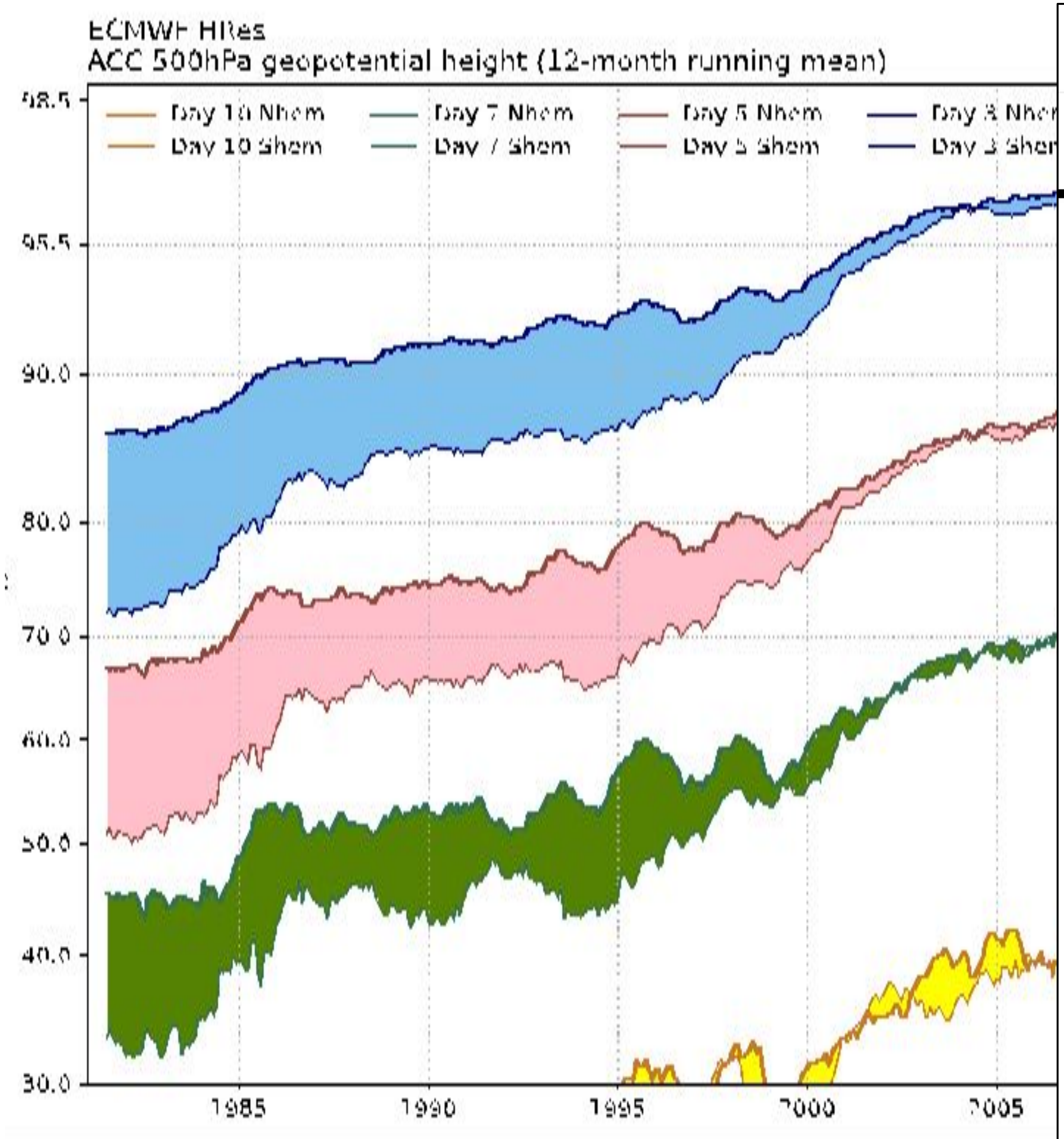
Earth system modelling is currently experiencing disruptive changes offering great opportunities.

1980-2020: The quiet revolution



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The quiet revolution of numerical weather prediction

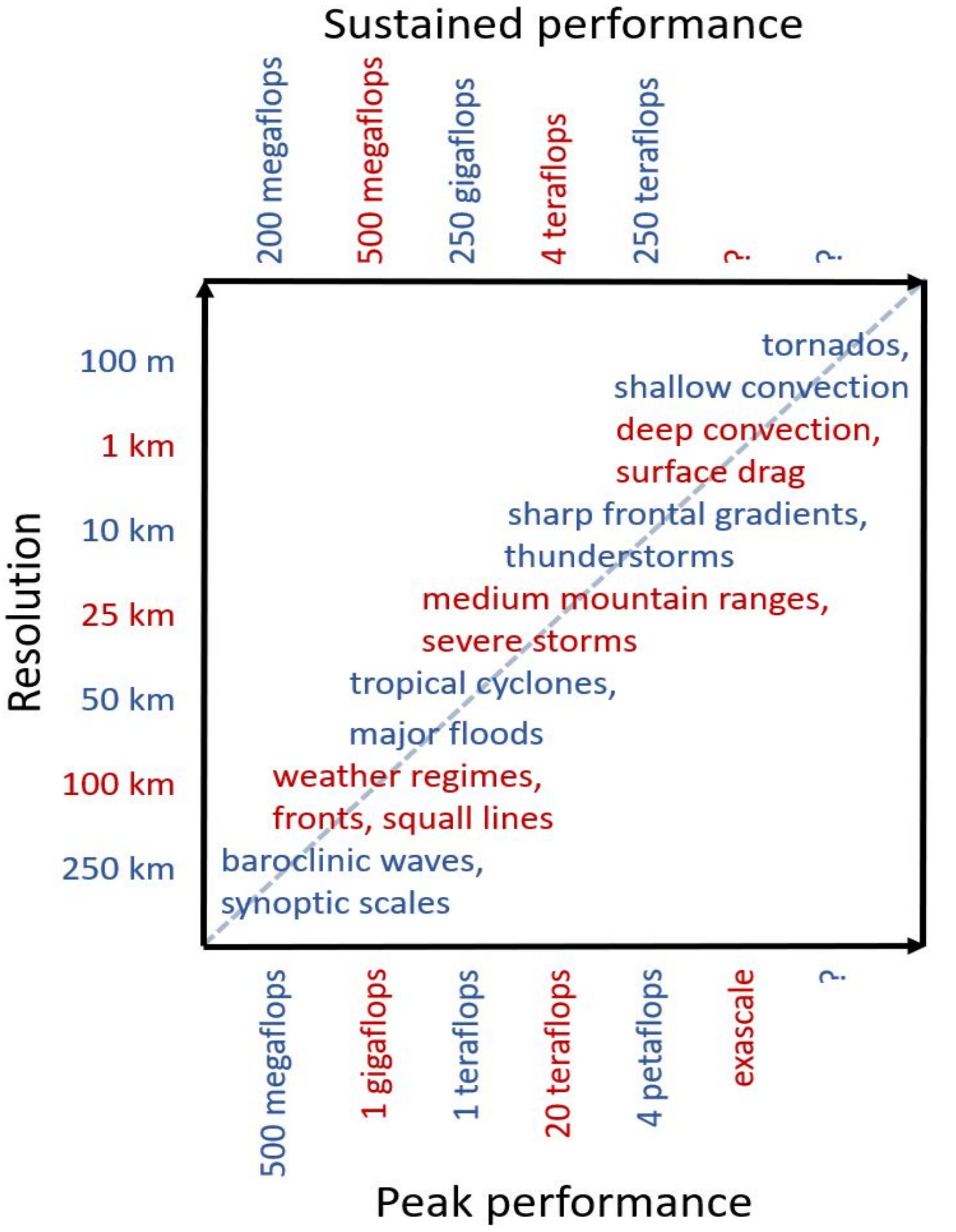
Peter Bauer, Alan Thorpe & Gilbert Brunet

Nature **525**, 47–55 (2015) | Cite this article

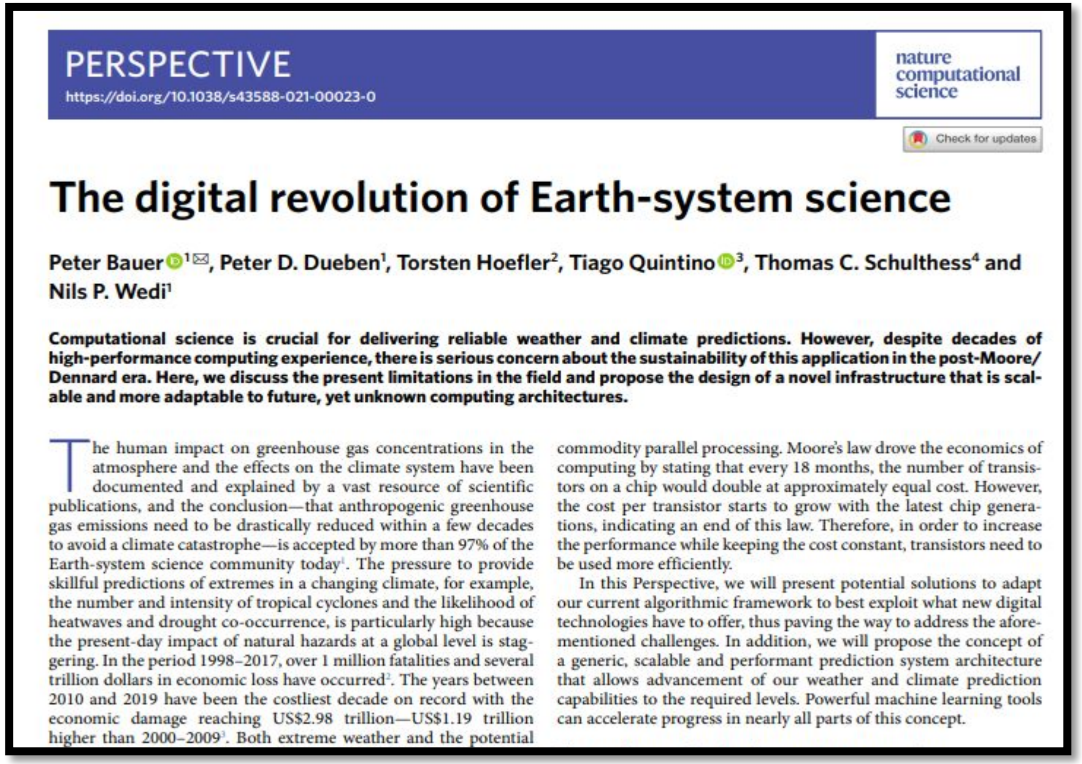
Abstract

Advances in numerical weather prediction represent a quiet revolution because they have resulted from a steady accumulation of scientific knowledge and technological advances over many years that, with only a few exceptions, have not been associated with the aura of fundamental physics breakthroughs. Nonetheless, the impact of numerical weather prediction is among the greatest of any area of physical science. As a computational problem, global weather prediction is comparable to the simulation of the human brain and of the evolution of the early Universe, and it is performed every day at major operational centres across the world.

2015-today: The digital revolution



Adapted from Neumann et al. Phil Trans A 2018



PERSPECTIVE
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nature computational science

Check for updates

The digital revolution of Earth-system science

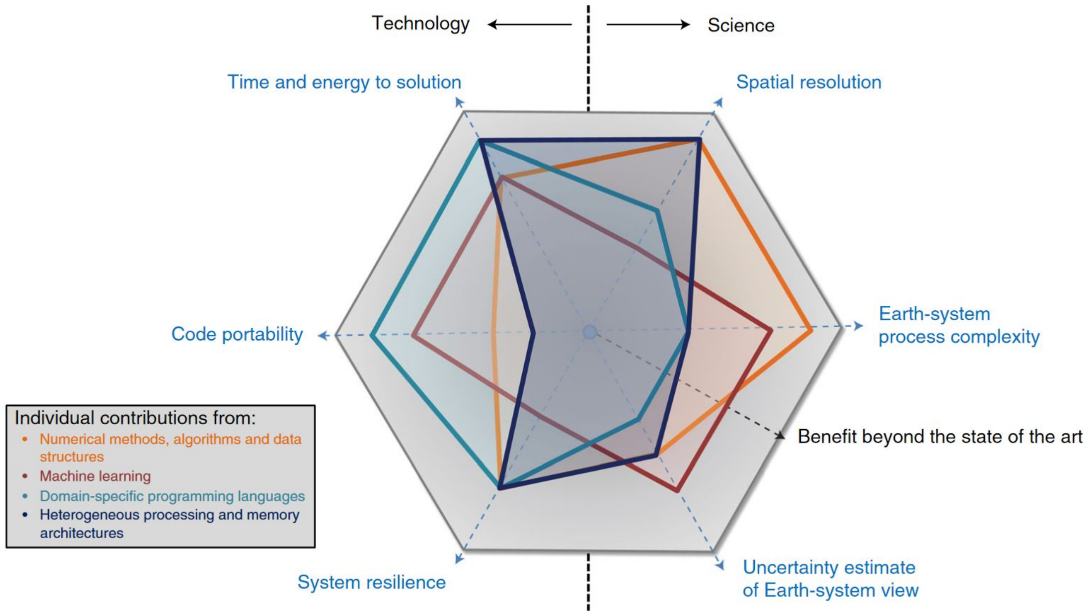
Peter Bauer[1], Peter D. Dueben[1], Torsten Hoefler[2], Tiago Quintino[3], Thomas C. Schulthess[4] and Nils P. Wedi[1]

Computational science is crucial for delivering reliable weather and climate predictions. However, despite decades of high-performance computing experience, there is serious concern about the sustainability of this application in the post-Moore/Dennard era. Here, we discuss the present limitations in the field and propose the design of a novel infrastructure that is scalable and more adaptable to future, yet unknown computing architectures.

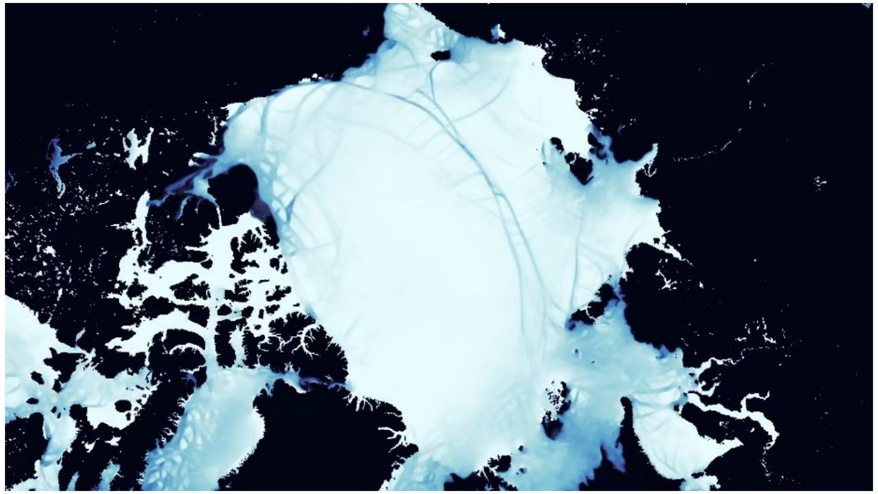
The human impact on greenhouse gas concentrations in the atmosphere and the effects on the climate system have been documented and explained by a vast resource of scientific publications, and the conclusion—that anthropogenic greenhouse gas emissions need to be drastically reduced within a few decades to avoid a climate catastrophe—is accepted by more than 97% of the Earth-system science community today[1]. The pressure to provide skillful predictions of extremes in a changing climate, for example, the number and intensity of tropical cyclones and the likelihood of heatwaves and drought co-occurrence, is particularly high because the present-day impact of natural hazards at a global level is staggering. In the period 1998–2017, over 1 million fatalities and several trillion dollars in economic loss have occurred[2]. The years between 2010 and 2019 have been the costliest decade on record with the economic damage reaching US$2.98 trillion—US$1.19 trillion higher than 2000–2009[3]. Both extreme weather and the potential

commodity parallel processing. Moore's law drove the economics of computing by stating that every 18 months, the number of transistors on a chip would double at approximately equal cost. However, the cost per transistor starts to grow with the latest chip generations, indicating an end of this law. Therefore, in order to increase the performance while keeping the cost constant, transistors need to be used more efficiently.

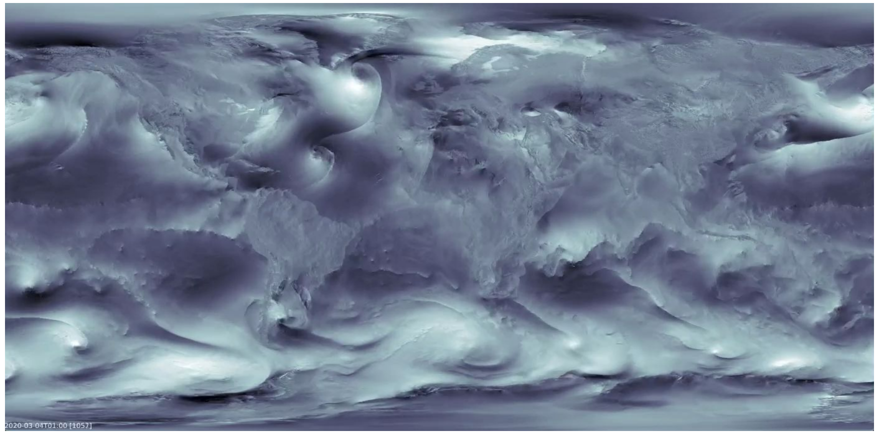
In this Perspective, we will present potential solutions to adapt our current algorithmic framework to best exploit what new digital technologies have to offer, thus paving the way to address the aforementioned challenges. In addition, we will propose the concept of a generic, scalable and performant prediction system architecture that allows advancement of our weather and climate prediction capabilities to the required levels. Powerful machine learning tools can accelerate progress in nearly all parts of this concept.



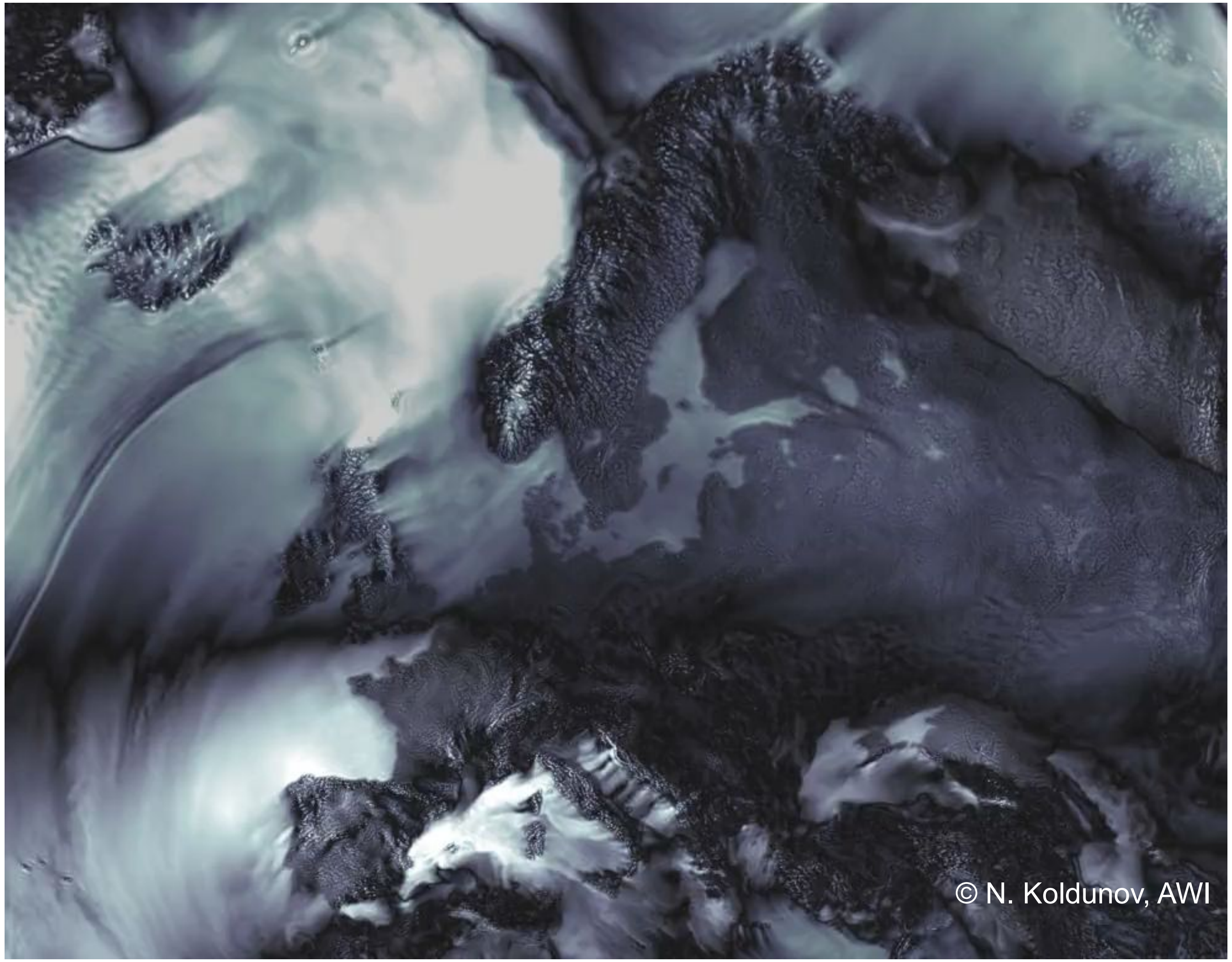
2015-today: The digital revolution to allow for km-scale models



More realistic at local scale



More realistic at global scale



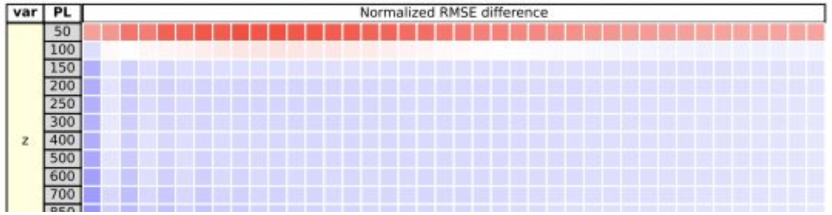
Better results via a coupled model system

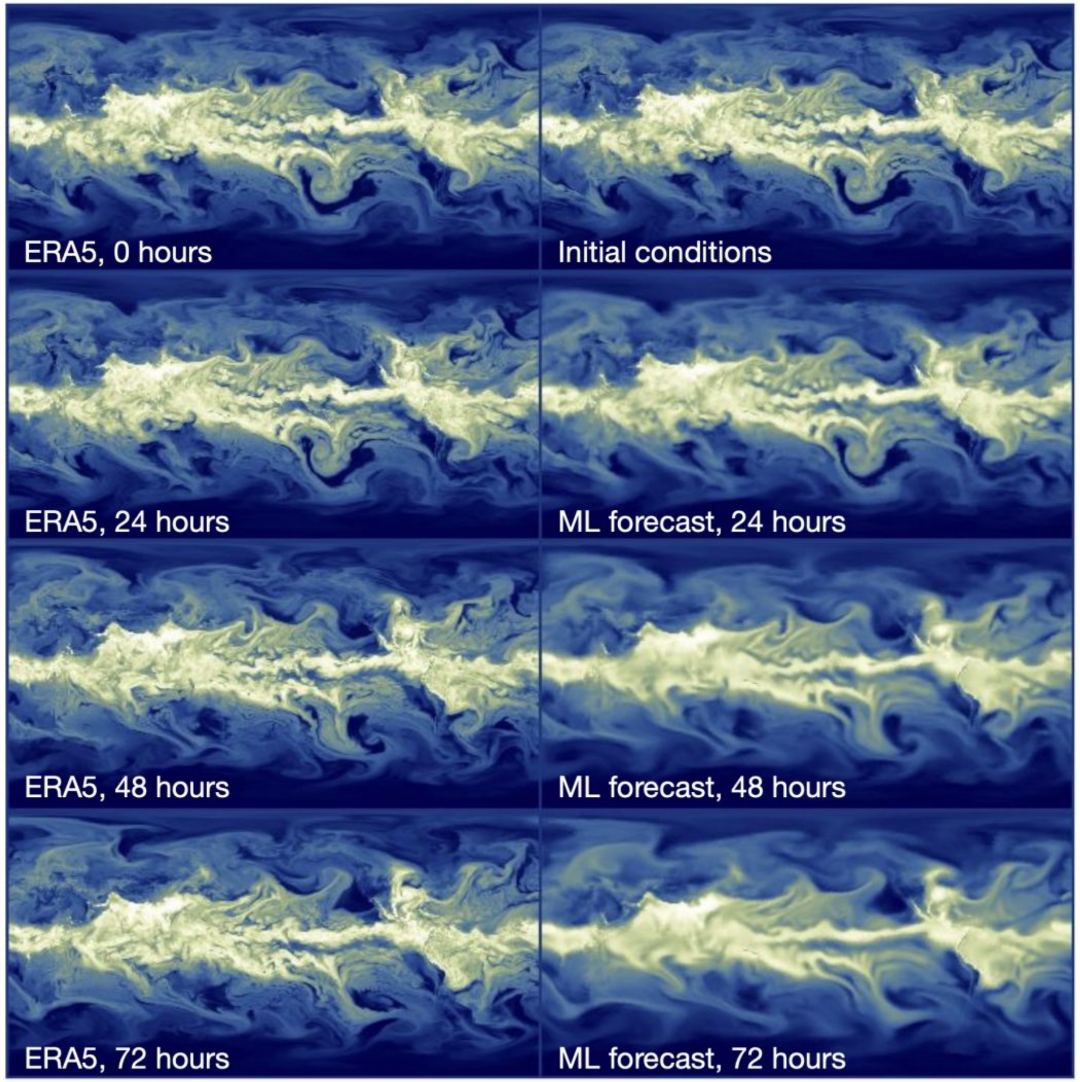
Global km-scale models improve realism of simulations significantly and are now becoming available.

And there is machine learning…

Can we also build entire forecast models with machine learning?

2022-today: The machine learning revolution





GraphCast from Google Deepmind, Fourcastnet from NVIDIA and Pangu-Weather from Huawei are beating conventional weather forecast model in deterministic scores and are orders of magnitudes faster.

But how do these models actually work?

In 2023 we still had many questions:
Can they avoid the smearing out for long predictions?
Can they learn uncertainty?
Can they extrapolate and faithfully represent extreme events?
Can they represent physically consistent forecasts?
Can they do data assimilation?

Images from Keisler (2022)

2022-today: The machine learning revolution

arXiv > physics > arXiv:2307.101

Physics > Atmospheric and Oceanic

[Submitted on 19 Jul 2023]

The rise of data-driven w

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Data-driven modeling based on machine
some applications. The uptake of ML met
revolution' of weather forecasting. The co
increasing model resolution and ensembl
forecasts that require much lower compu
standard NWP-based forecasts in an oper
verification tools to assess to what extent
of a forecast from one of the leading glob
when verified against both the operationa
drawbacks of ML-based forecasts. A new
initialization and model training.

Subjects: **Atmospheric and Oceanic Physics (phy**
Cite as: arXiv:2307.10128 **[physics.ao-ph]**
(or arXiv:2307.10128v1 **[physics.ao-ph]**
https://doi.org/10.48550/arXiv.2307.10

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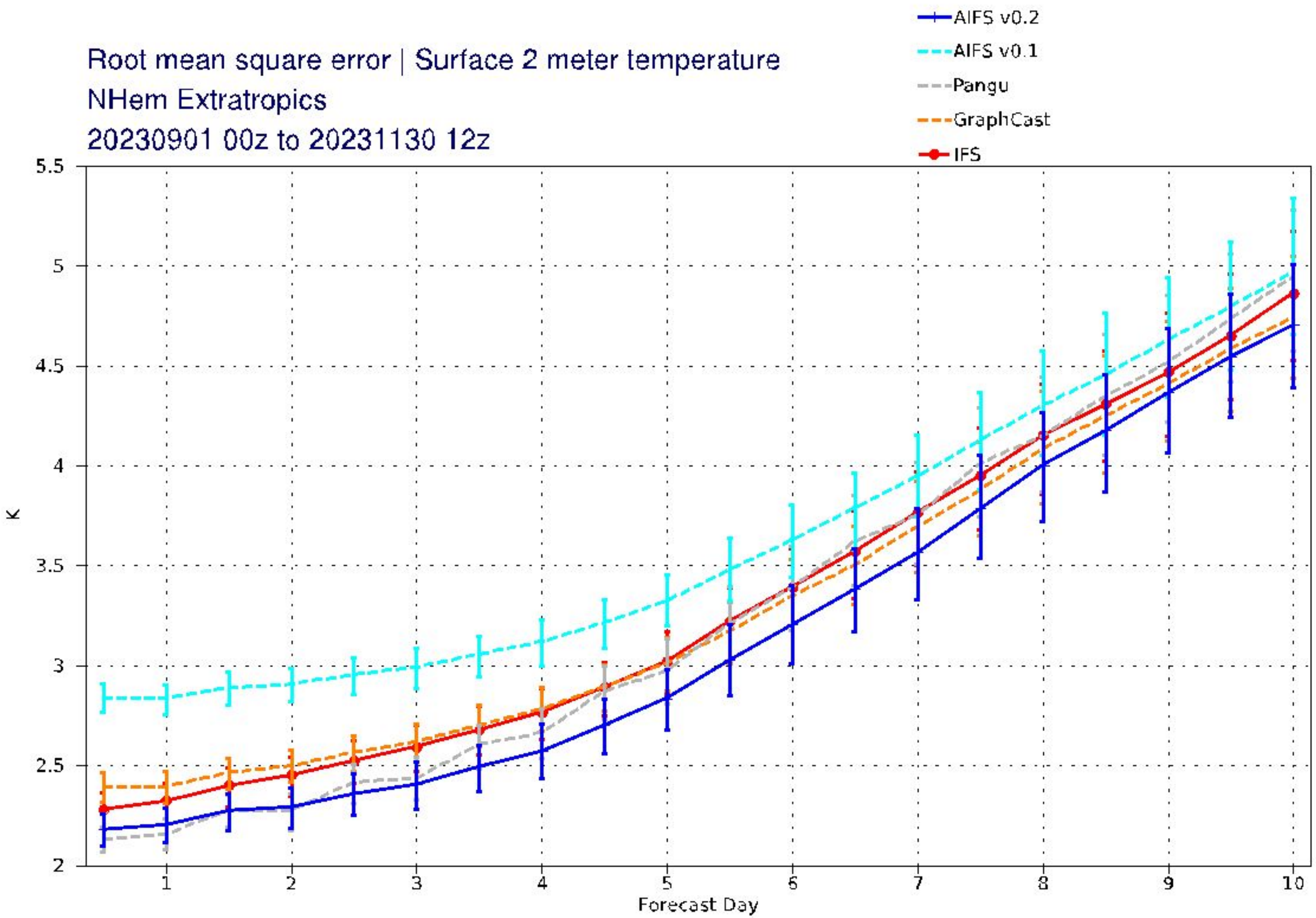
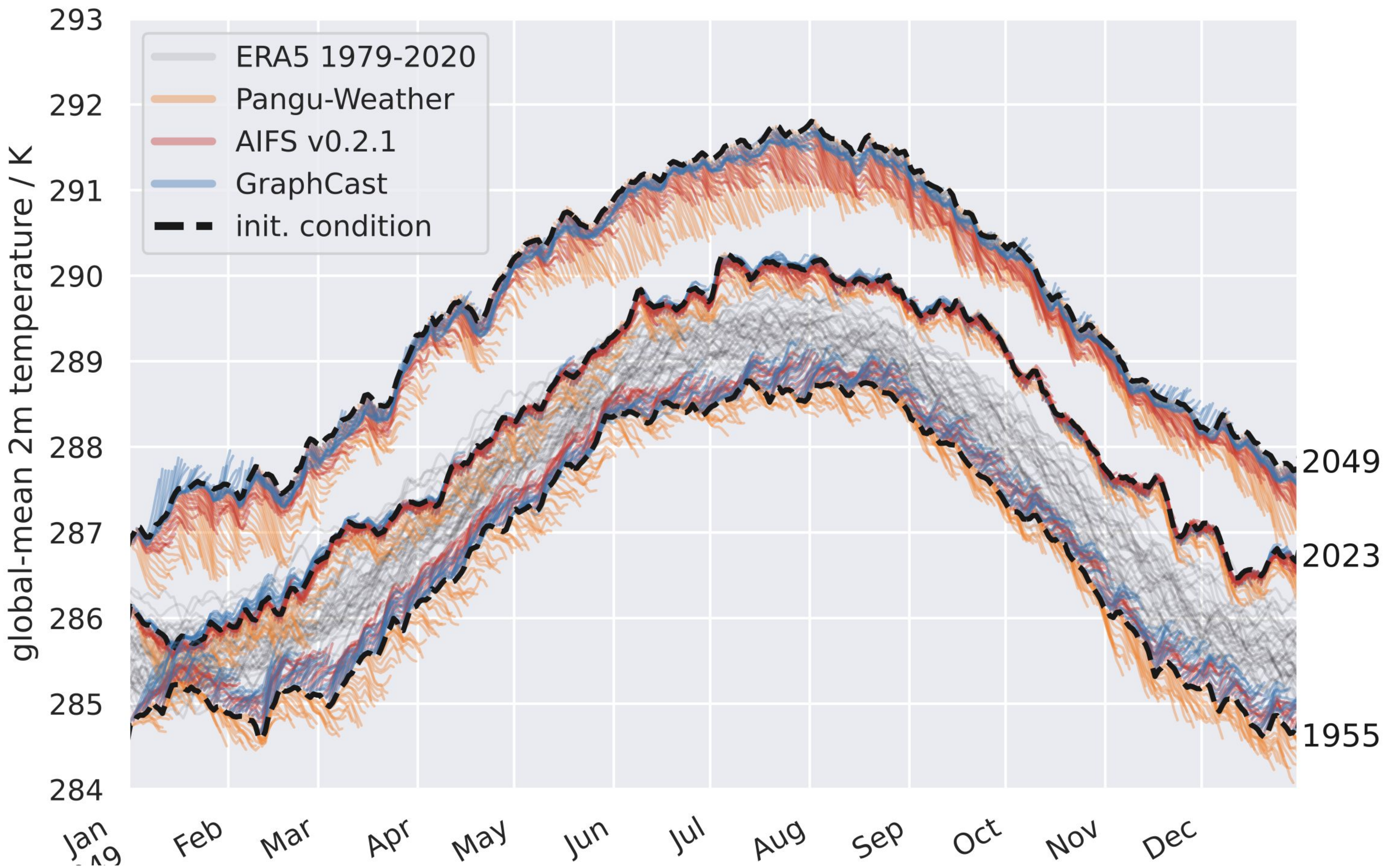


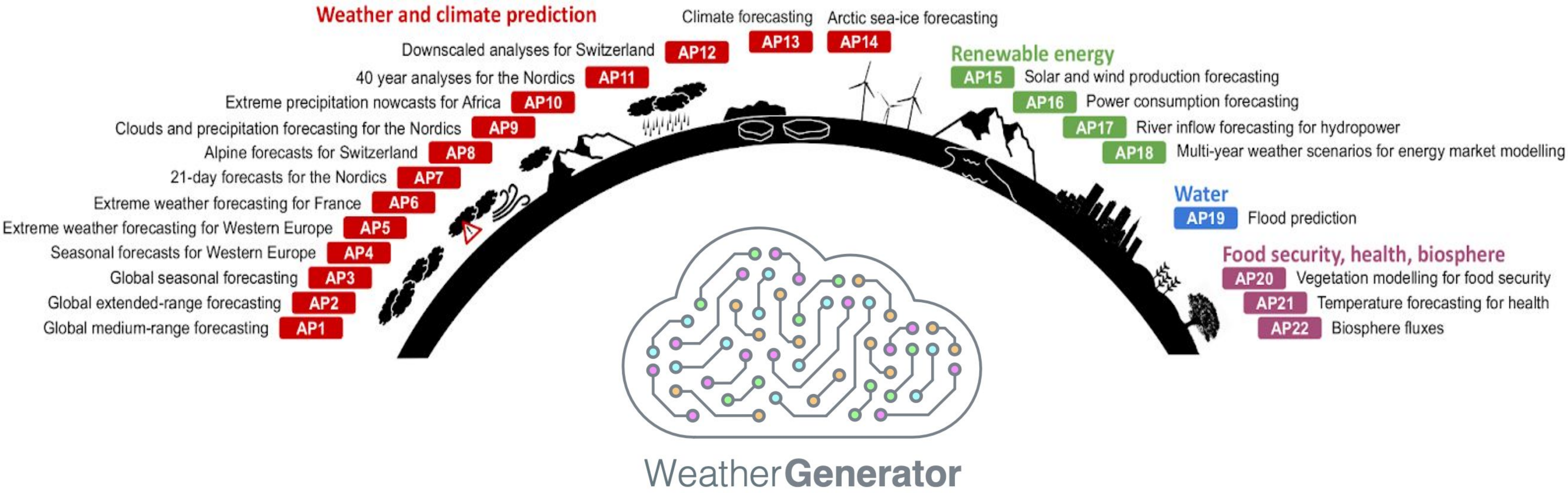
Lang et al. ECMWF Newsletter 2024 and the AIFS team

Next step: Machine learned climate simulations?



Rackow et al. in preparation

WeatherGenerator – A foundation model for weather and climate



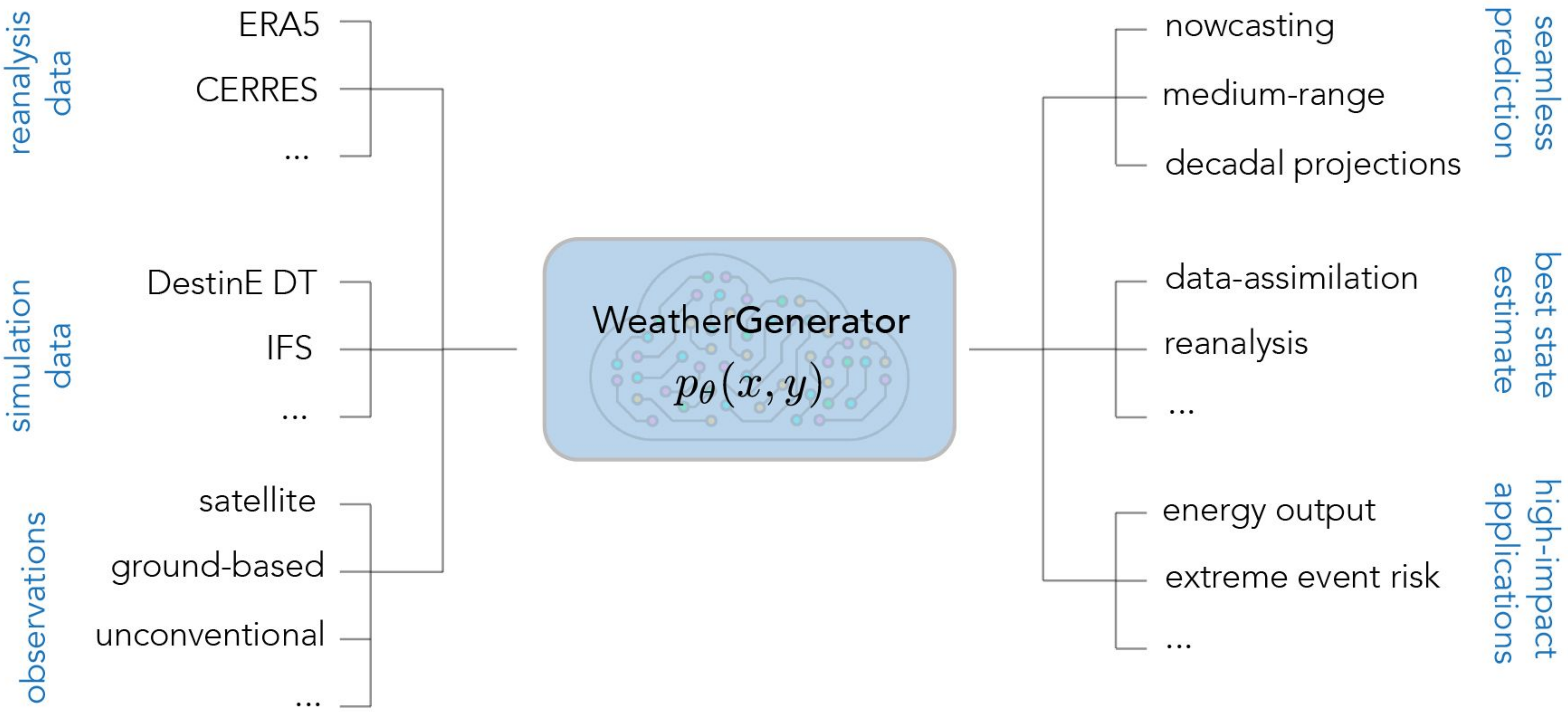
What about a unification of the machine learning applications via a Foundation Model for Earth system science?

We will not start from scratch as we have AtmoRep (Lessig et al. 2023) and other research initiatives.

Aim: This project will build the machine-learned WeatherGenerator – the world's best generative Foundation Model of the Earth system – that will serve as a Digital Twin in Destination Earth (DestinE).

https://www.ecmwf.int/en/about/media-centre/news/2024/weathergenerator-project-aims-recast-machine-learning-earth-system

WeatherGenerator – A foundation model for weather and climate



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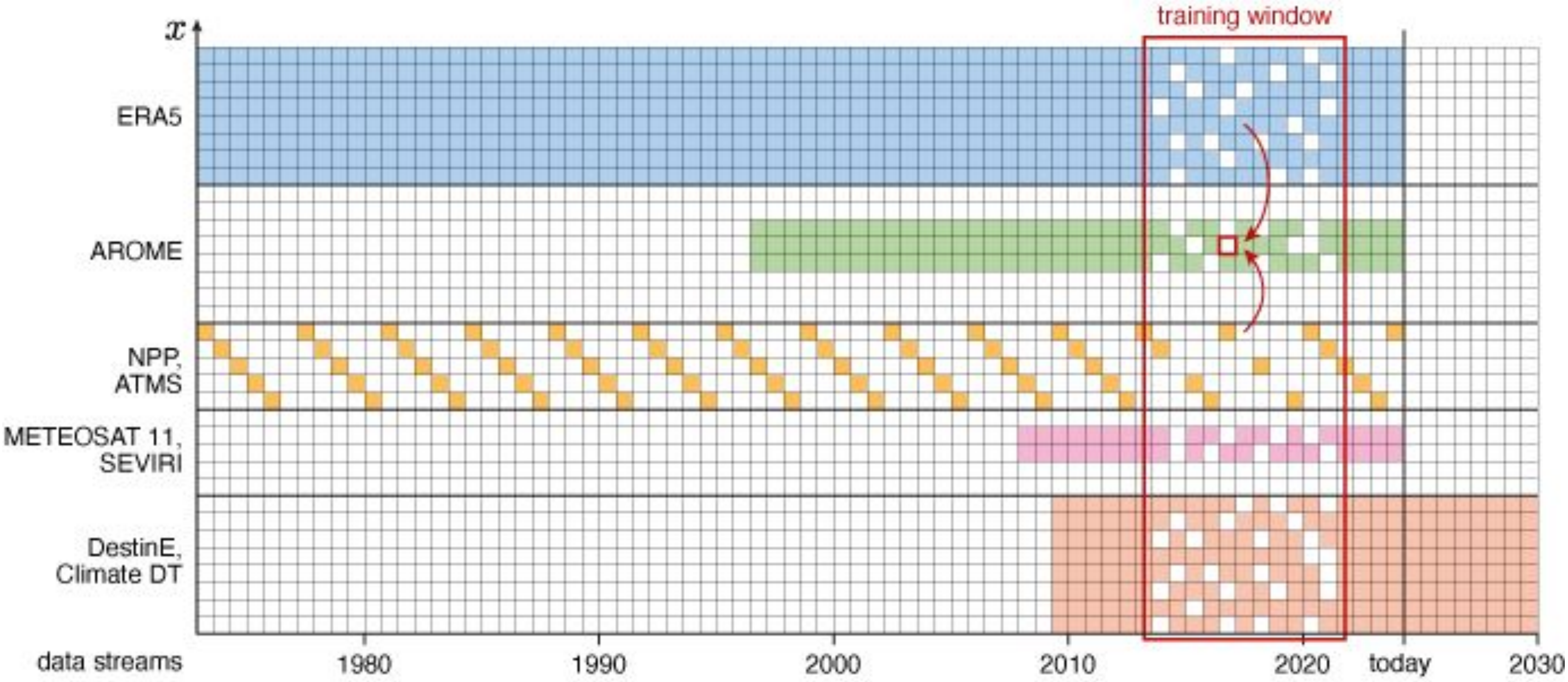
Next steps: Foundation models for weather and climate



https://www.ecmwf.int/en/about/media-centre/news/2024/weathergenerator-project-aims-recast-machine-learning-earth-system

2022-today: The machine learning revolution – A timeline

2018 – Machine learned modes used for tests in weather and climate

2019 – Machine learned models used in hybrid approaches

2021 – Machine learned models used for nowcasts

2022 – Machine learned models beat deterministic forecast models

2023 – Machine learning models beat ensemble forecast models
Machine learning models can do AMIP simulations

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2024 – Machine learning models can do data assimilation

2025 – Machine learning models can do Earth system modelling with ocean/sea-ice/waves/land

2026 – Machine learning models can do climate simulations
Machine learning models are run as foundation models

What have we learned?

The quiet revolution (1980-2020):

- Steady investment into Earth system modelling and Earth system observations made a difference.

The digital revolution (2015-today):

- Conventional models need to be made future proof via new software and hardware standards.
- Large projects such as DestinE make km-scale models possible today and will make a difference.

The machine learning revolution (2022-today):

- Models such as AIFS can beat physics-based models for deterministic and ensemble predictions.
- There is loads of interesting science to explore regarding hybrid models and predictability.
- We may soon see machine learning models that can do data assimilation and climate modelling.

The next step: Models will be better, tools will be easier, and data/HPC will be federated

- We will build a European Earth system and a European foundation model for Earth system science.
- To achieve this needs programmes such as Destination Earth.

Many thanks! **Peter.Dueben@ecmwf.int**

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