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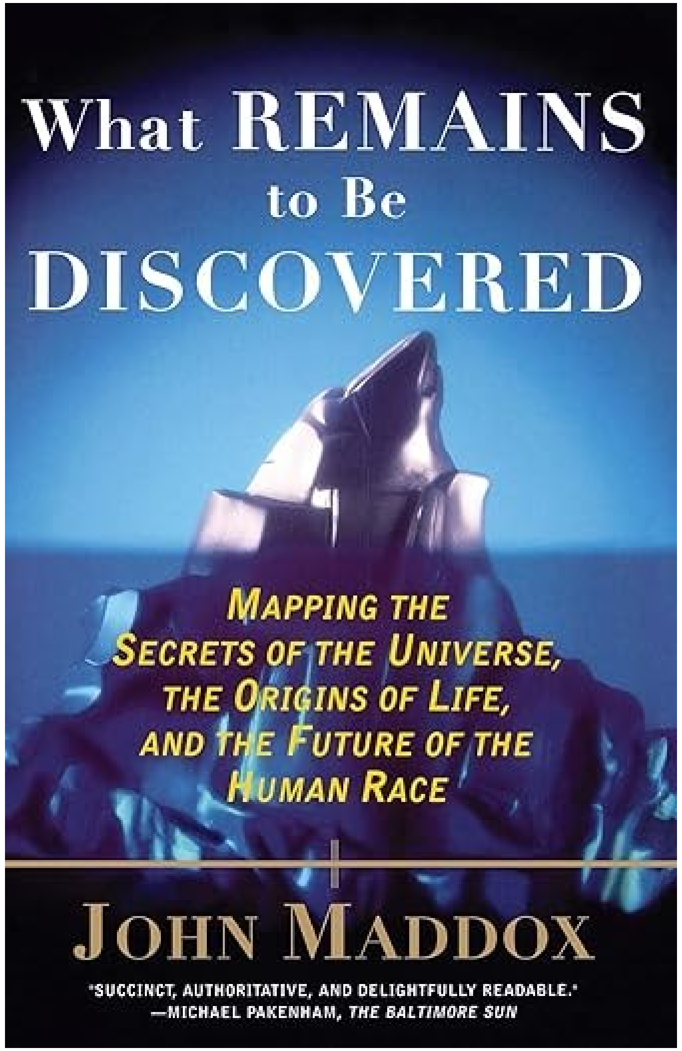
Simulating weather and climate
From a quiet revolution to fast and furious

Stephen Belcher,

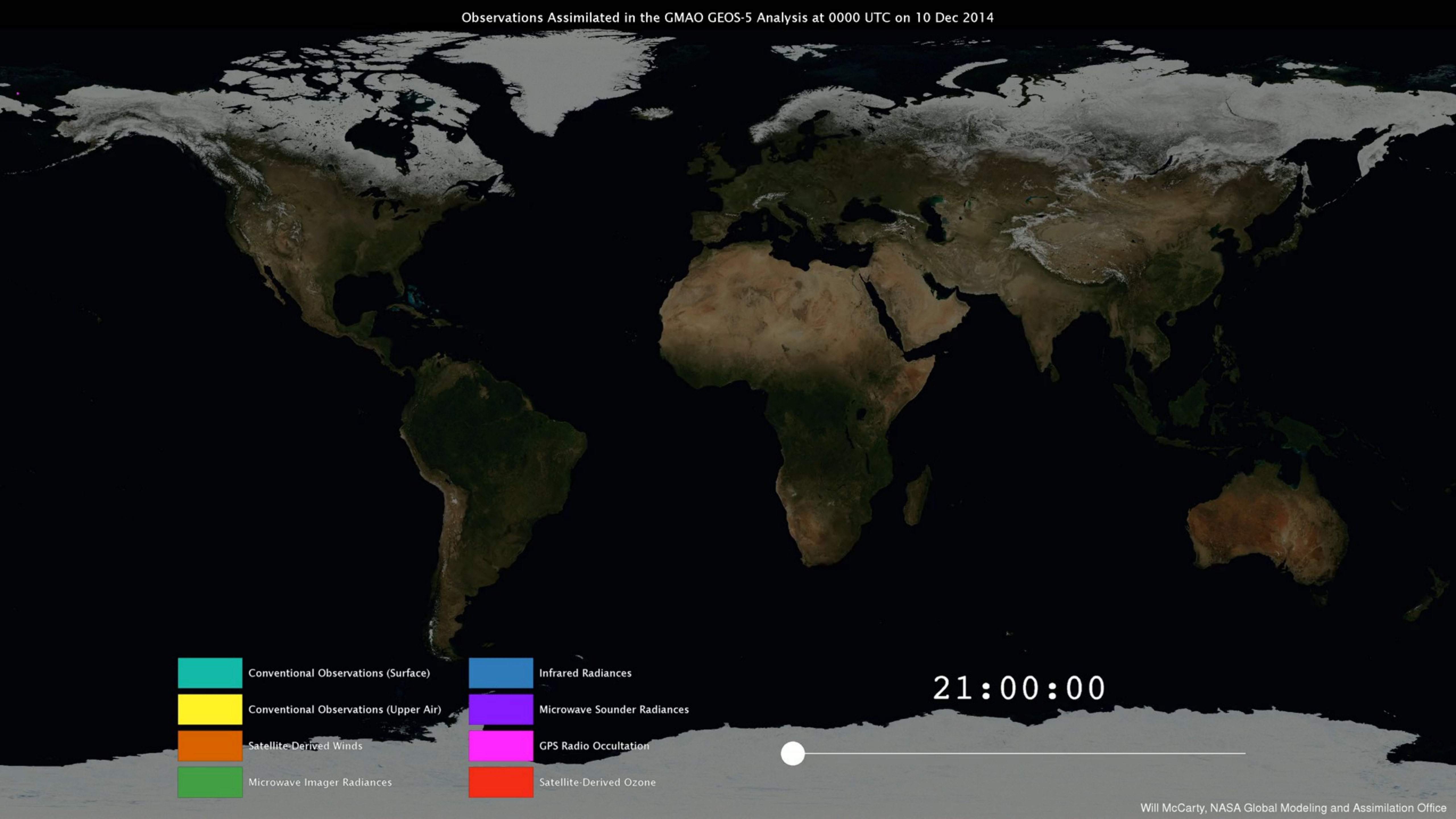
Met Office Chief Scientist

New Directions in Theoretical Physics

Edinburgh, January 6th 2026



- Priorities Maddox identified in 1999
  - Very large
  - Very small
  - Very complex


Observations Assimilated in the GMAO GEOS-5 Analysis at 0000 UTC on 10 Dec 2014
Conventional Observations (Surface)
Conventional Observations (Upper Air)
Satellite-Derived Winds
Microwave Imager Radiances
Infrared Radiances
Microwave Sounder Radiances
GPS Radio Occultation
Satellite-Derived Ozone
21:00:00
Will McCarty, NASA Global Modeling and Assimilation Office

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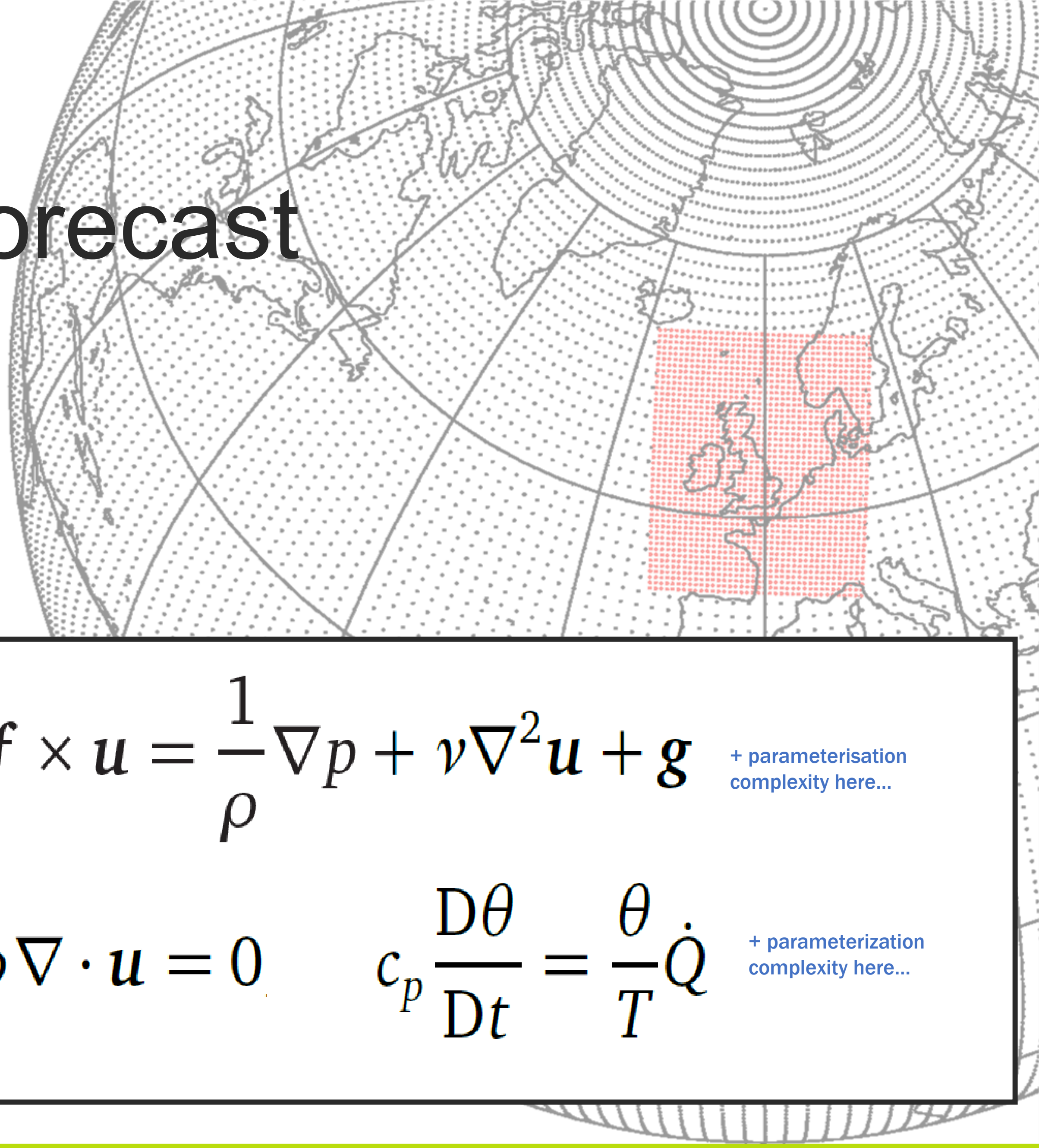
How to make a weather forecast



Integrate to future state of atmosphere and oceans:

- Discretised Navier Stokes equations of motion on a rotating sphere
- “Physics” parameterisation: thermodynamics + radiation + moisture + clouds
- Boundary conditions at land, sea and ice

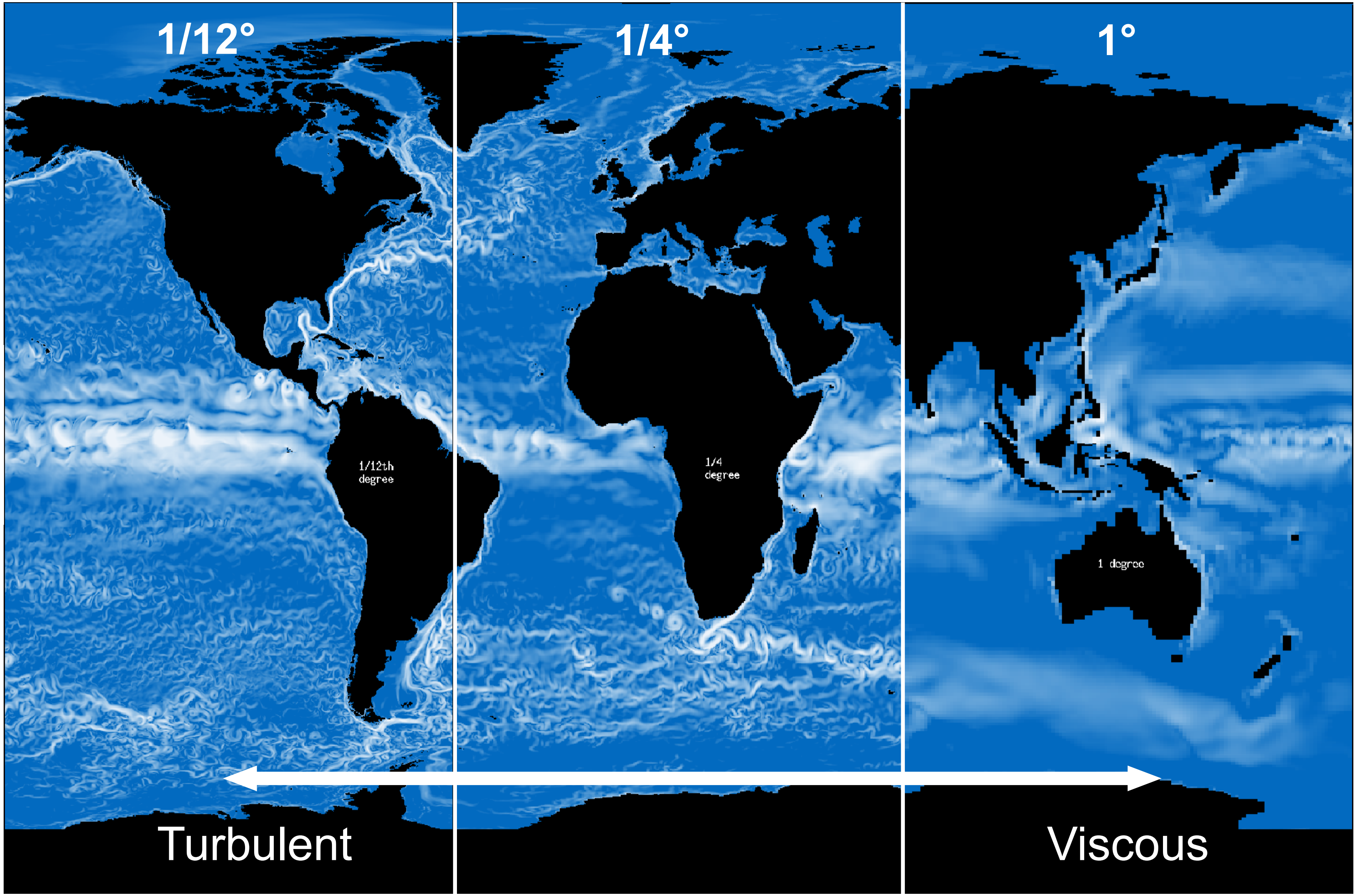
$$\frac{\mathrm{D}\boldsymbol{u}}{\mathrm{D}t} + \boldsymbol{f} \times \boldsymbol{u} = \frac{1}{\rho}\nabla p + \nu\nabla^2\boldsymbol{u} + \boldsymbol{g}$$

+ parameterisation complexity here...

$$\frac{\mathrm{D}\rho}{\mathrm{D}t} + \rho\nabla\cdot\boldsymbol{u} = 0 \qquad c_p\frac{\mathrm{D}\theta}{\mathrm{D}t} = \frac{\theta}{T}\dot{Q}$$

+ parameterization complexity here...

Resolved 'dynamics'



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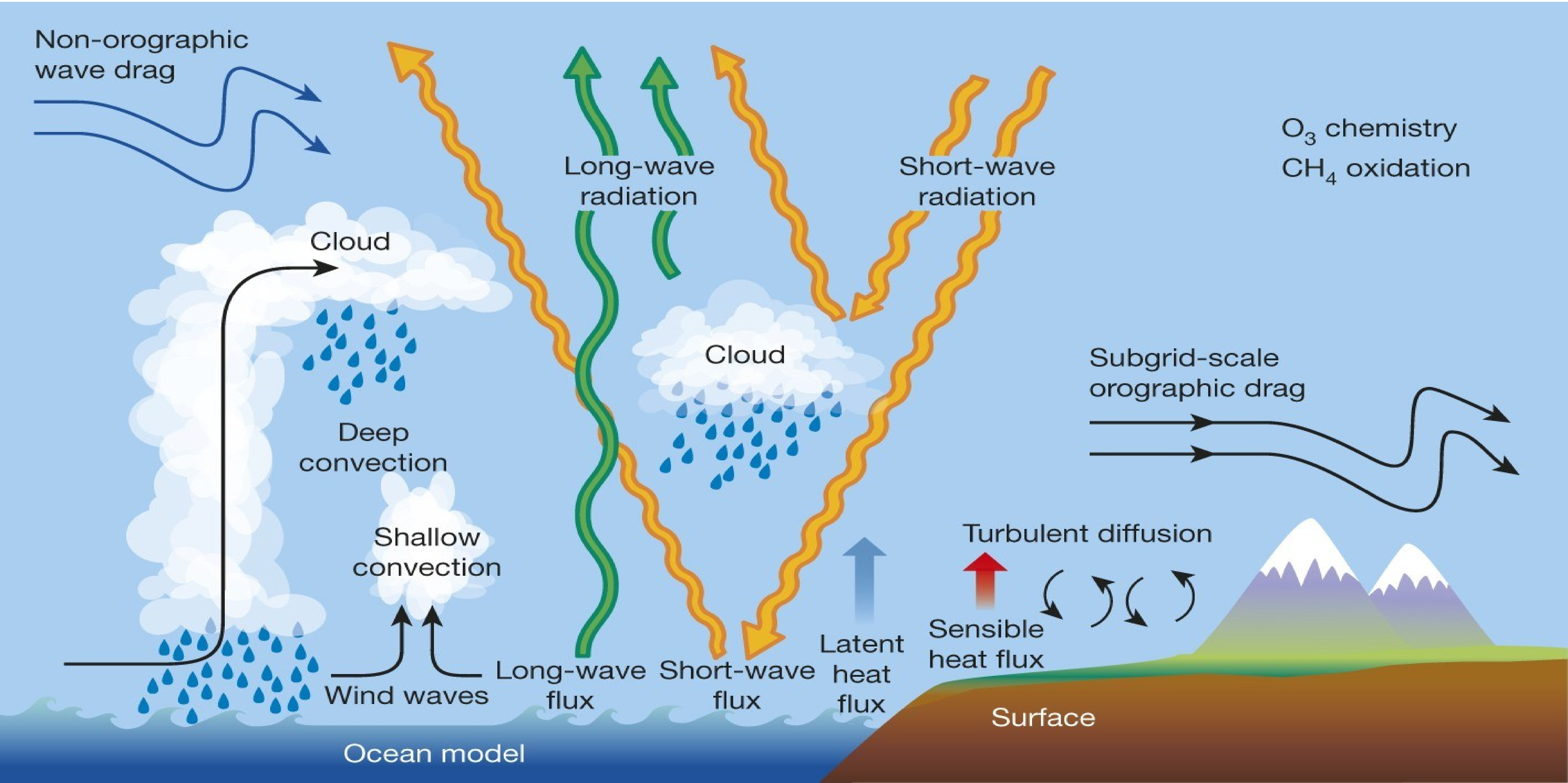
“Physics” parameterisation



Compute requirements

The 00Z Forecast cycle:

Data Assimilation: **10,000 Cores** for 30min

Model Run: **45,000 Cores** for 2hrs

Run 24x7: resilience to CPU and other system failures

Timeliness: Integrations must fit the operational window

HPC1 / HPC2	HPC3 / HPC4
2 HPE Cray EX4000 **904,320 Cores** 2.2 PB RAM 41 PB Storage Managed service in Microsoft Azure	2 HPE Cray EX4000 **904,320 Cores** 2.2 PB RAM 48 PB Storage Managed service in Microsoft Azure

Met Office Supercomputers

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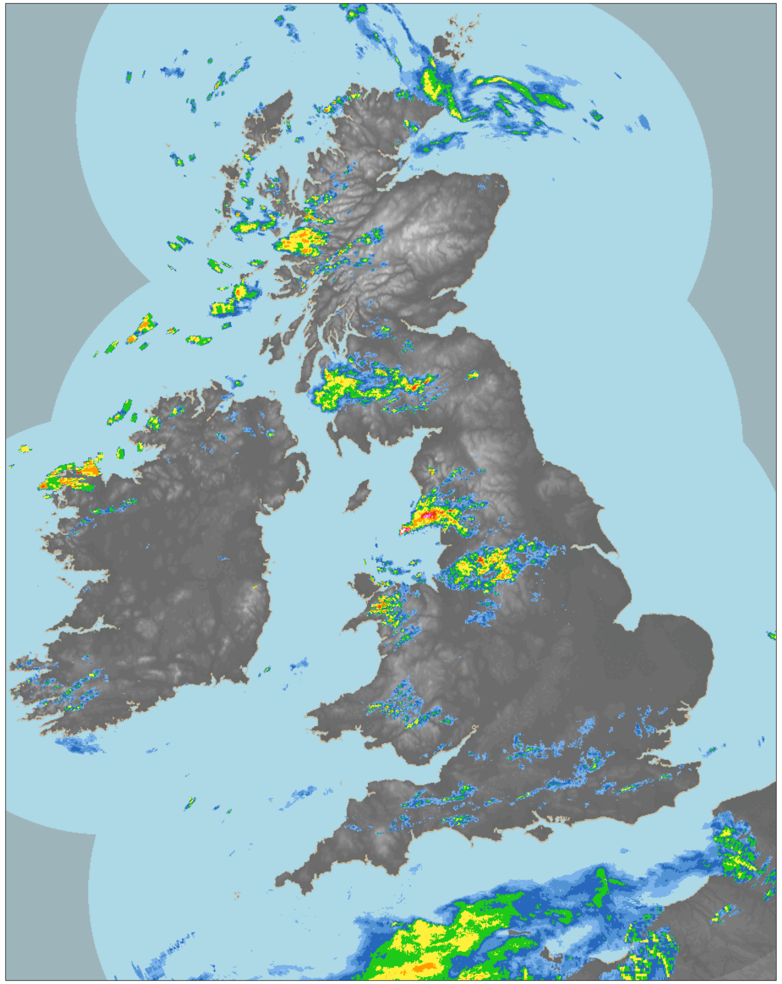
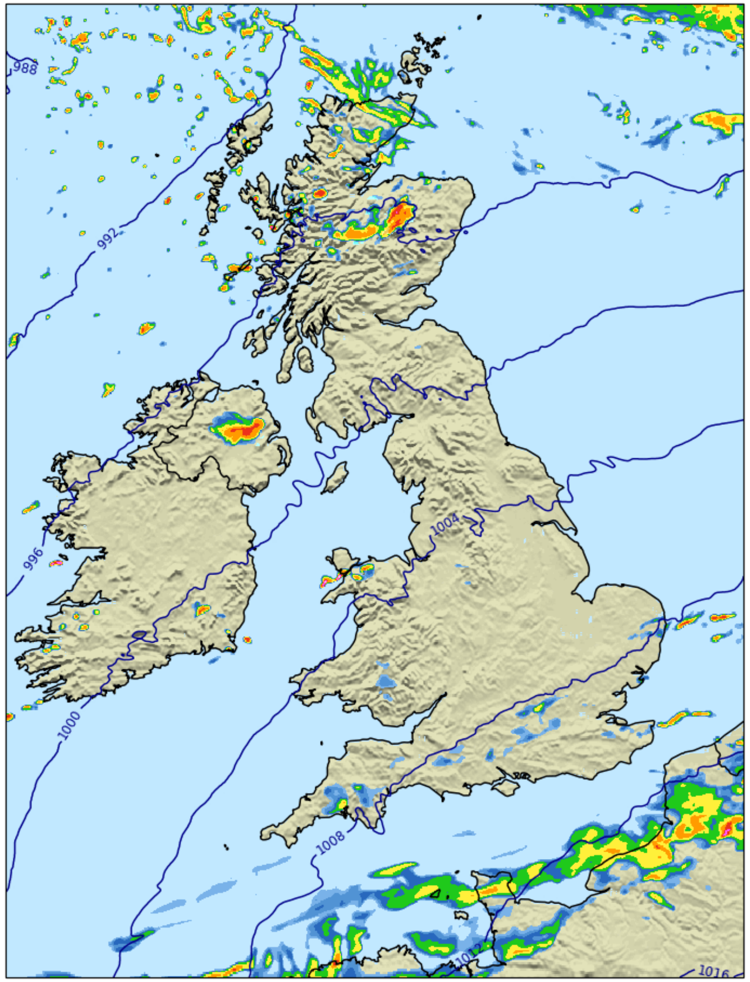
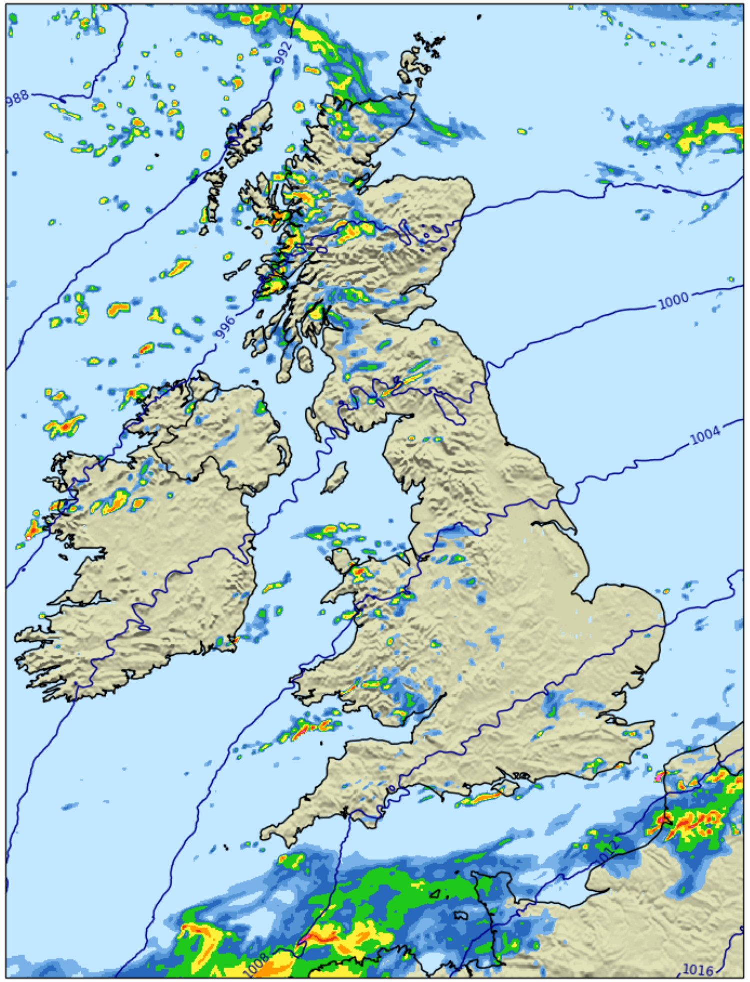
High Resolution Storm Resolving Forecasts – Storm Bram



Storm Bram, 8/9 Dec 2025.
Radar Observations

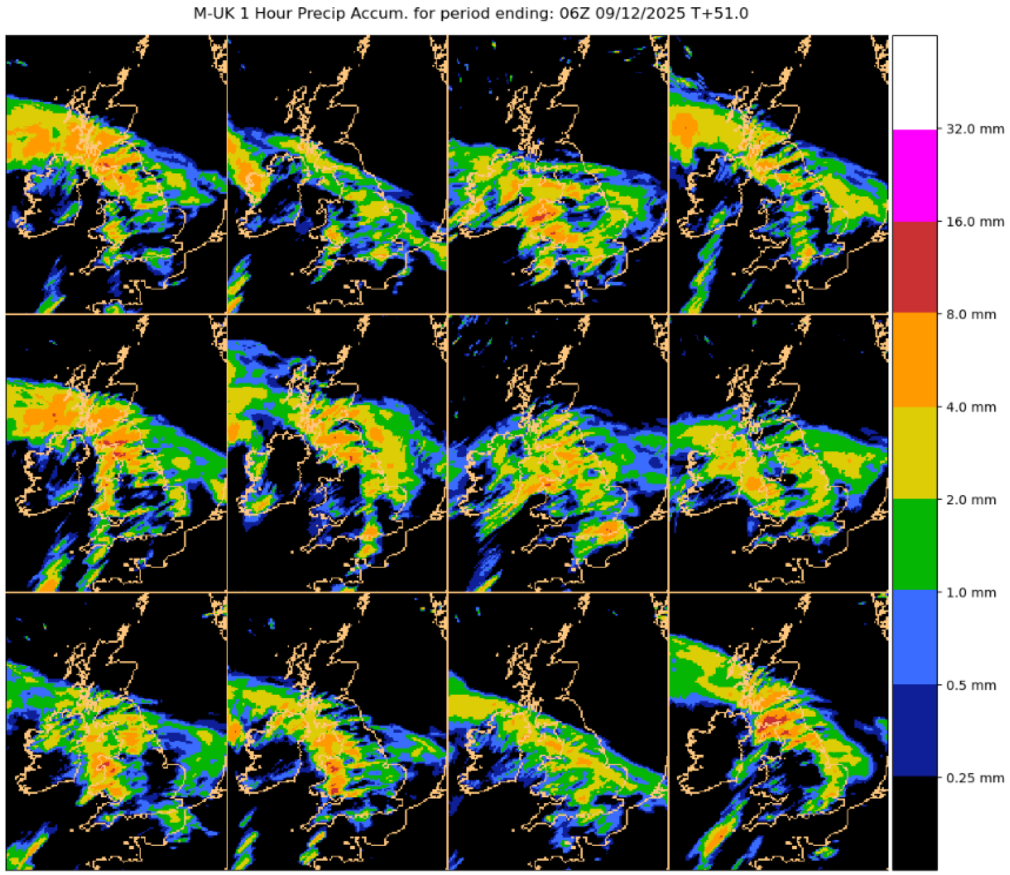


Storm Bram, *init 15Z 8 Dec 2025*
OS 46 [T+1 to T+32]



Storm Bram, *init 15Z 8 Dec 2025*
PS 47 [T+1 to T+32]

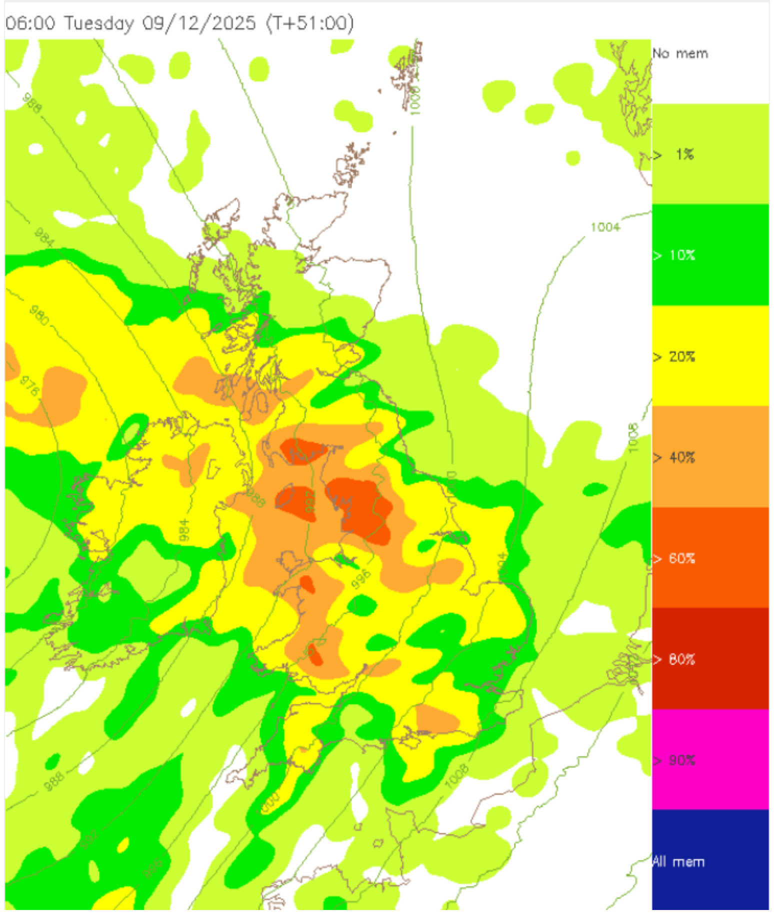
Ensemble Forecasts:
forecasting the accuracy of the forecast



MOGREPS-UK Ensemble Member Precip (mm/hr)

Post

processing



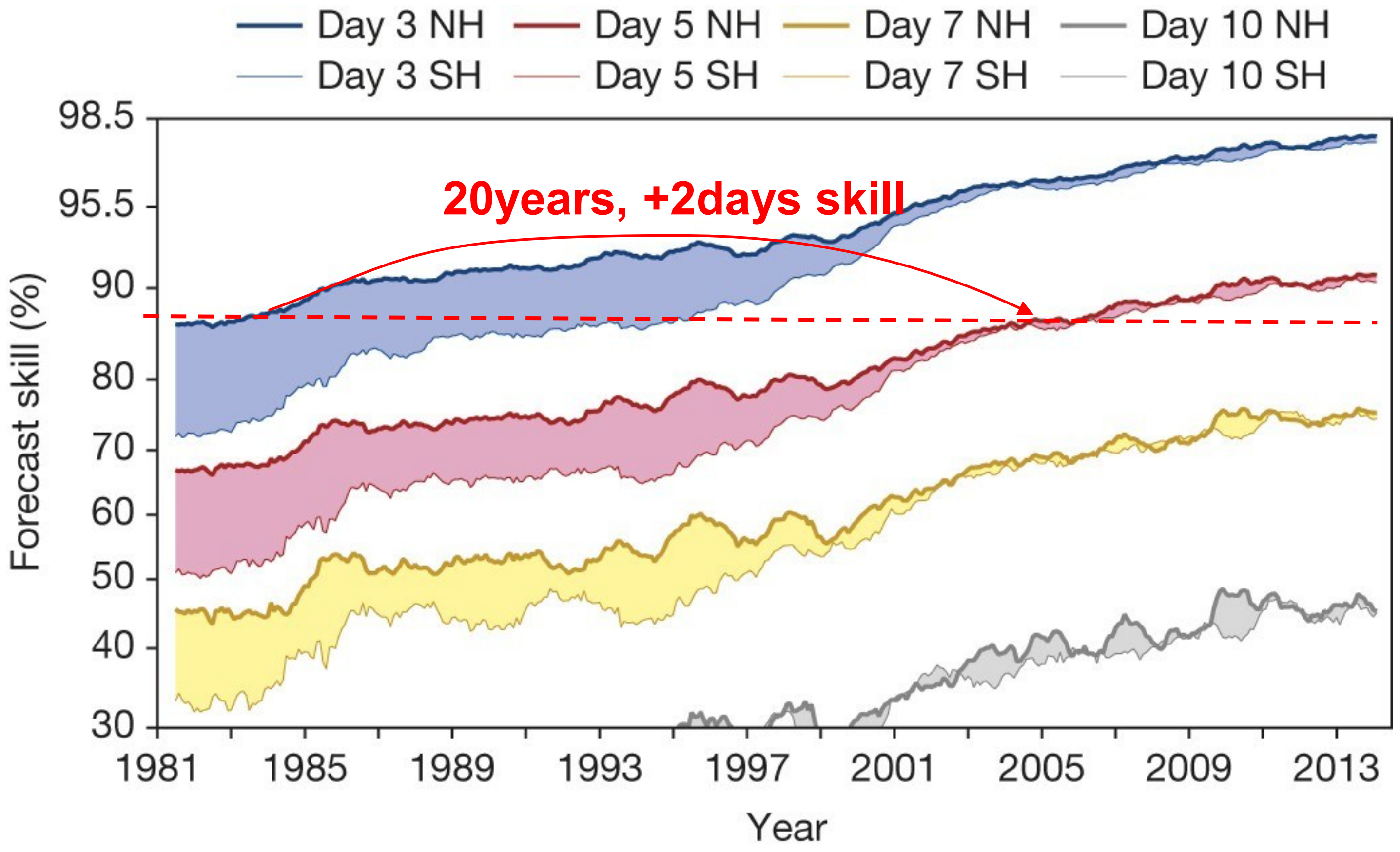
IMPROVER Probability of Precip >4mm/hr

Storm Bram: 3-day forecast for Tuesday December 9th 2025 06:00 GMT

A quiet revolution in numerical weather prediction

There has not been a "breakthrough"

But incremental model, observation and computer advances have delivered +1day/decade forecast skill for 30yrs



P Bauer *et al. Nature* **525**, 47-55 (2015) doi:10.1038/nature14956

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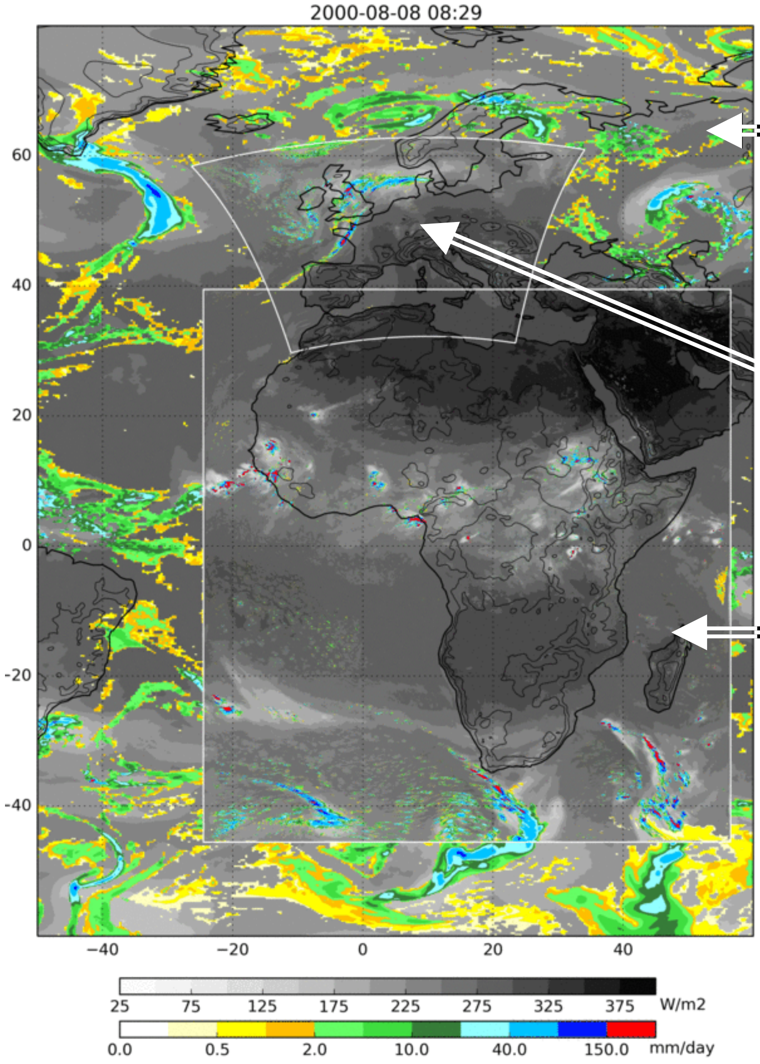
Challenge: km-scale climate models will need enormous computers (and energy)

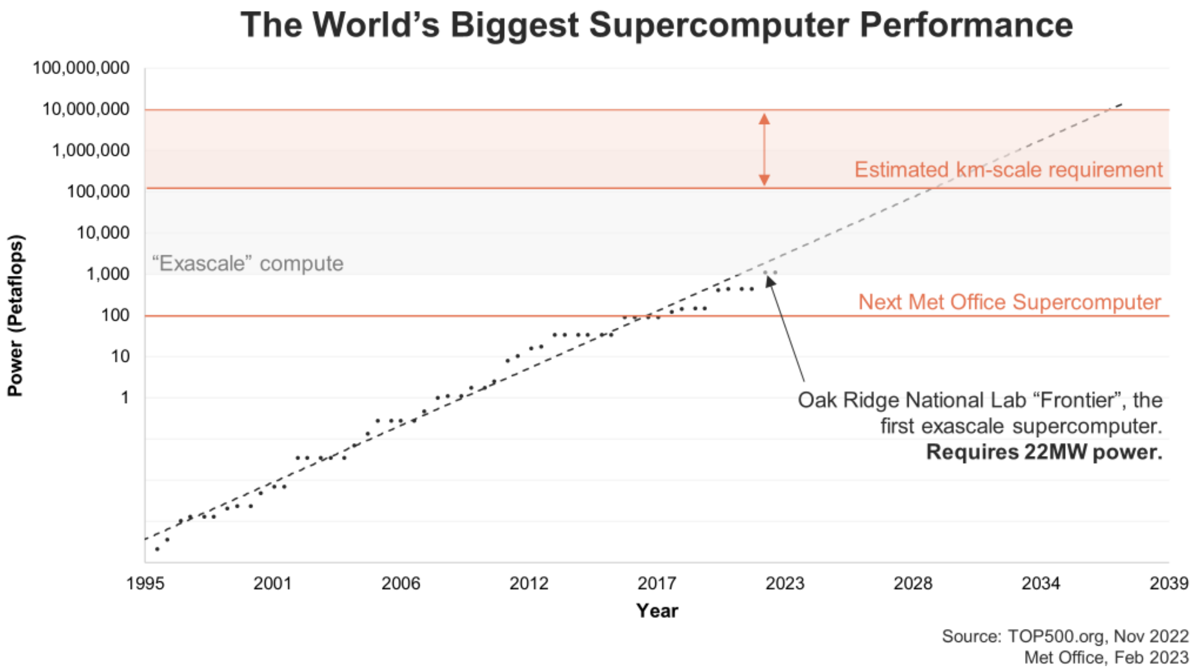


Global model (25km)
UKMO present day
+ future time-slice

Euro 2.2km
(1536 x 1536 x 70)

10-year simulations
Present day
+ future time-slice

CP4Africa 4.5km
(2000 x 2100 x 80)
10-year simulations
UKMO present day
+ future time-slice



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The revolution got fast and furious…

‘The model is fast to run. […] a single 6-hour model step takes 0.04 seconds when running on a NVIDIA A100 GPU, i.e. creating a 5-day forecast takes 0.8 seconds.’ – Keisler 2022.

Forecasting Global Weather with Graph Neural Networks

Ryan Keisler
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Abstract

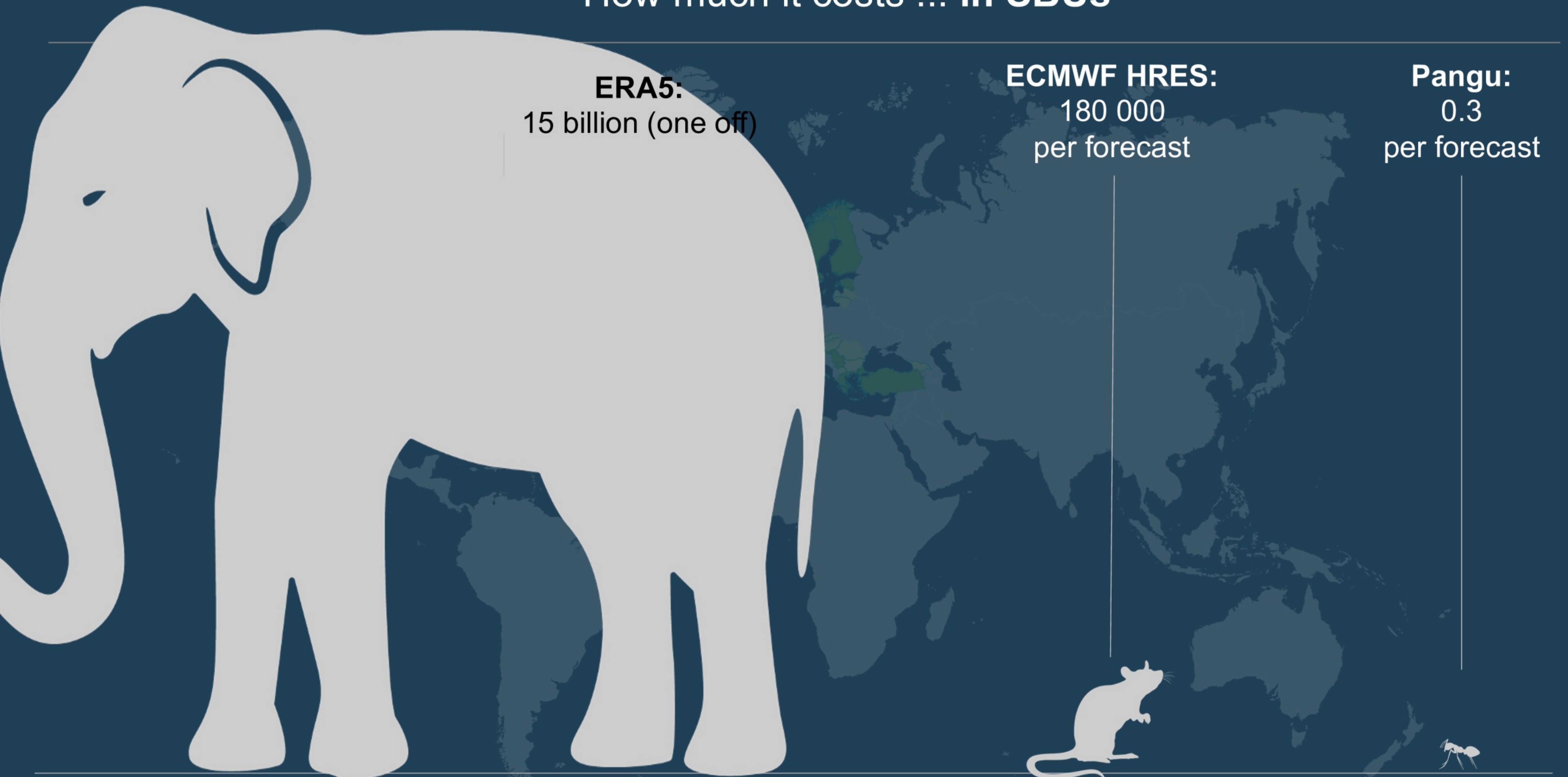
We present a data-driven approach for forecasting global weather using graph neural networks. The system learns to step forward the current 3D atmospheric state by six hours, and multiple steps are chained together to produce skillful forecasts going out several days into the future. The underlying model is trained on reanalysis data from ERA5 or forecast data from GFS. Test performance on metrics such as $Z500$ (geopotential height) and $T850$ (temperature) improves upon previous data-driven approaches and is comparable to operational, full-resolution, physical models from GFS and ECMWF, at least when evaluated on 1-degree scales and when using reanalysis initial conditions. We also show results from connecting this data-driven model to live, operational forecasts from GFS.

1 Introduction

Numerical weather prediction (NWP), as part of the broader weather enterprise, has had an enormous and positive impact on society. Decades of steady improvements in the quantity and types of observational data, better modeling techniques, and more computational power have resulted in increasingly accurate weather forecasts and growing adoption of NWP in real-world applications.

While statistical techniques have been used within NWP for decades, the core dynamical engines of these models continue to be based on the physical principles governing the atmosphere and ocean. More recently, spurred on by advancements in machine learning (ML), there has been a surge of interest in statistical, data-driven techniques for weather forecasting. The motivation for using ML is to improve upon an already extremely successful NWP program through some combination of better forecasts, faster forecasts, or more forecasts, i.e. larger ensembles. There may also be opportunities for using ML to advance our scientific understanding of the underlying physical processes [Cranmer et al., 2020].

How much it costs ... **in SBUs**



Graphic courtesy of ECMW

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Blending – Used as an umbrella term:

There are different ways of realising the 'optimal blend' of physical and machine learning (ML) methods for weather and climate prediction.

A selection of examples are given as illustration.

Hybrid – Two distinct categories are defined for ways in which ML is blended within the prediction step

Independent-physics-based

Separate from ML model

- Global Ensemble NWP as a direct data feed
- Global Climate Prediction and Projections
- Targeted use cases, e.g. dispersion model
- Regional model embedded within global NWP

Integrated-ML

ML active within the physical model

- ML inside the Data Assimilation (DA) scheme
- ML inside the parametrizations in the physical model ("emulation" or "enhancement")
- ML trained inside the dynamical core of the model ("system aware ML")

Composite-ML

Blending while the prediction system is running

- Global MLWP "nudging" the Global physical model on the large scale
- Global MLWP driving regional physical model
- Global physical model driving regional cllimate ("downscaler")

Augmented-ML

Blending outside the prediction system

- Combining MLWP and physical model ensemble members to create a blended output
- ML creating new outputs using physical model input, e.g. lightning diagnostic
- ML used to enhance or correct physics-based outputs

Independent-ML

Separate from the physics-based model

- Global Ensemble MLWP as a direct data feed
- Direct-from-observations prediction (DOP)
- MLWP targeted for a specific use case, e.g. tropical cyclones, visibility
- Regional ML embedded within Global Climate model

NWP = Numerical Weather Prediction
MLWP = Machine Learning Weather Prediction

Physics-based component | ML component | Physics-based and/or hybrid

ML and seasonal forecasting

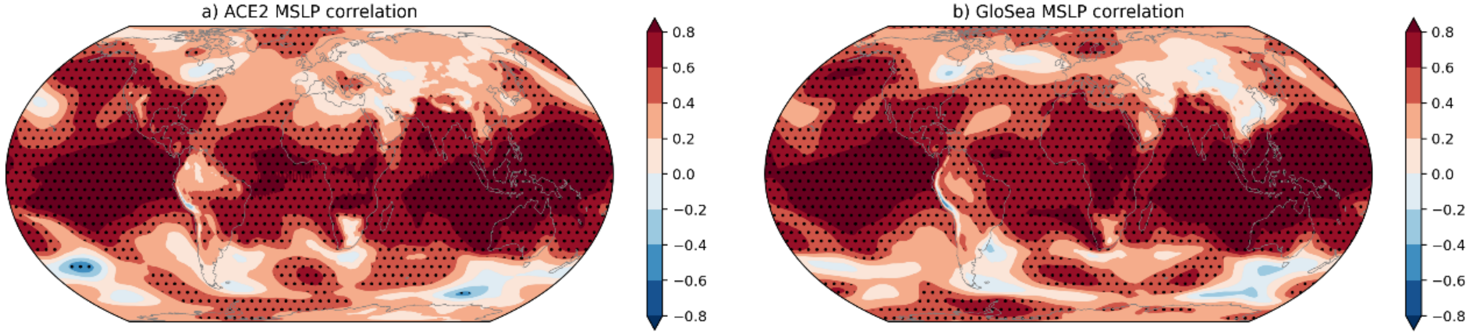


Figure: ***DJF correlation against ERA5 for ACE2 (left) and GloSea (right)***

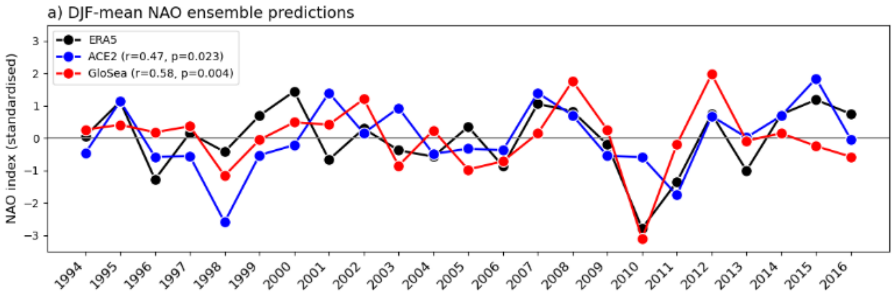


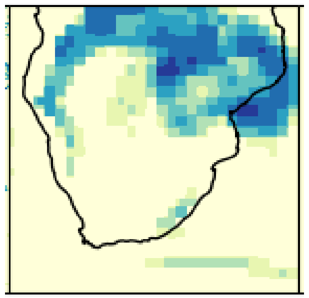
Figure: ***DJF NAO index 1994-2016 for ERA5, ACE2 and GloSea***

- **First demonstration of data-driven skilful global seasonal forecasts**
- Initialise ACE2 ML model (Allen Institute for AI) in early November → assess DJF conditions
- Patterns of skill align remarkably well with GloSea
- Regional skill (e.g. NAO), error and spread also align well with dynamical models
- ML model is orders of magnitude faster to run!
- New opportunities for developing, producing and understanding near-term climate predictions

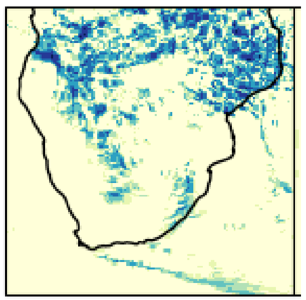
Kent et al., 2025 npj Climate & Atmospheric Science: https://doi.org/10.1038/s41612-025-01198-3

AI Downscaling

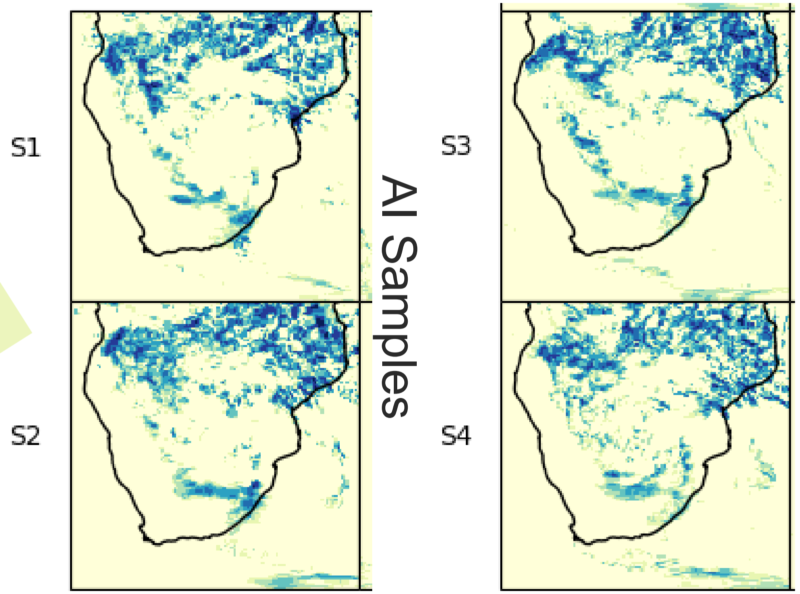
1. Most weather and climate predictions/projections are based on global model data



2. Traditionally, Regional Simulations (RCMs) translate global information to local scales, but can take more than a year to produce



3. New AI methods, trained on existing RCMs, can rapidly translate global information at a fraction of the cost/time.



Southern African application, shown here, produced by Simon Tucker

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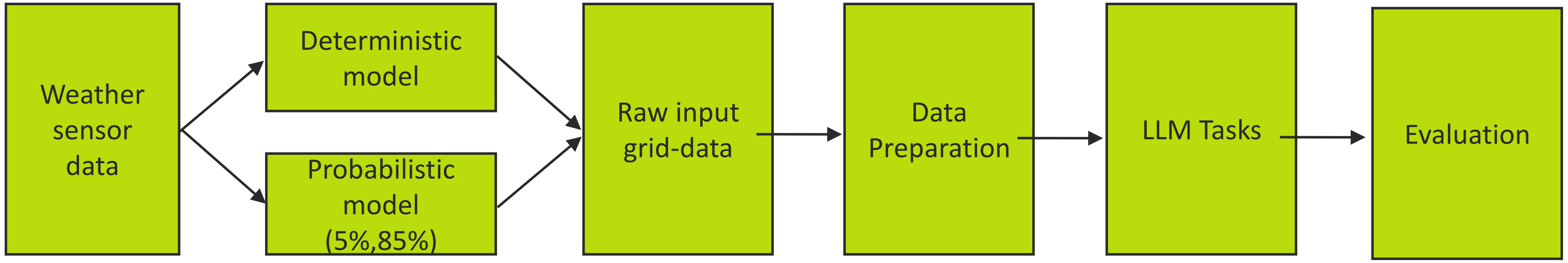
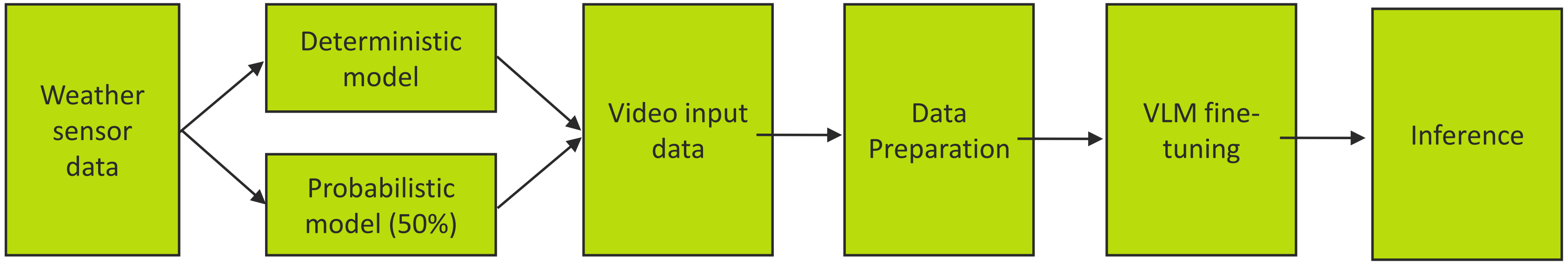
AI Shipping Forecast

https://arxiv.org/pdf/2512.03623

LLM Generation Algorithm: Logic



VLM Generation Algorithm: Logic



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What is the forecast for weather and climate?

People: New skills mix

- Physics
- Computer Science
- Data Science + AI
- Maths & Statistics

Physics: Continued need

- ‘Understanding’
- Training data for ML models in changing climate
- Climate change

AI: weather fast moving, climate in infancy

- Hybrid Physics + AI
- NWP from observations
- Downscaling
- Explainable AI

Operations: hybrid

- Parallel running
- Redesign production cycle
- Direct from obs
- K-scale climate

Thank you.

For more information please contact

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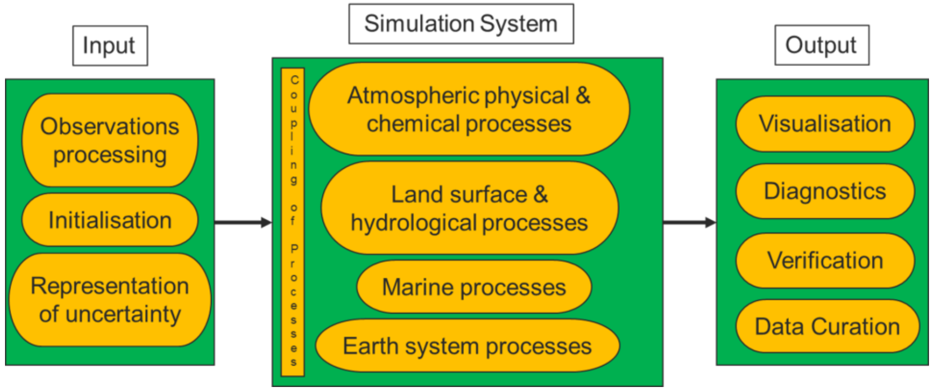
Challenge: physics parameterisations

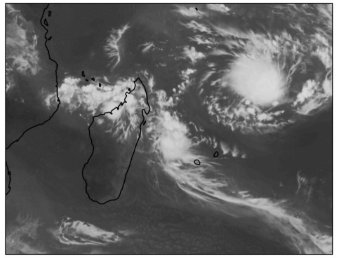
Convection: organised clouds and thunderstorms	Fluid dynamics and moist physics of clouds Role of aerosols in cloud formation and evolution
Ocean surface turbulence	Turbulent mixing in thin layer between atmosphere and deep ocean
Effects of cities on lower boundary condition	Fluid dynamics and thermodynamics of urban layers
Carbon cycle for climate runs:	Roles of vegetation and ocean biogeochemistry in oceans

Challenge: harness next-gen supercomputers

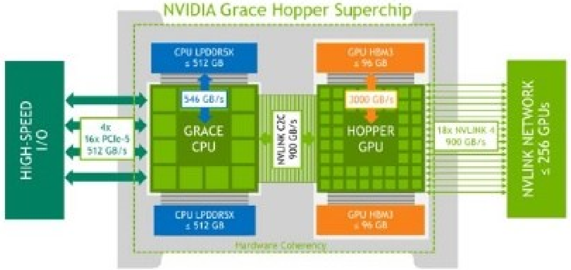
“To reformulate and redesign our complete weather and climate research and operational/production systems, including oceans and the environment, to allow the Met Office and its partners to fully exploit future generations of supercomputer for the benefits of society.”



Enable new science



Exploit new hardware (CPUs + GPUs)



Improved scalability & flexibility

Grow external collaborations

ExCALIBUR

Momentum™

The Unified Earth Environment Prediction Framework

What is a weather forecast?

Probability, confidence, impacts and guidance

National Capability

Observations → Prediction/ Projection → Post Processing → Data Supply →

Products and Services

Customer P. Processing → Production → Service Delivery → Customer Experience