Machine learning – a view from ECMWF

3rd ACCORD All Staff Workshop

Matthew Chantry

Victoria Bennett, Chris Kitchen, Peter Dueben, Linus Magnusson, Zied Ben Bouallegue
and many others

ECMWF

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Machine learning roadmap

https://www.ecmwf.int/en/elibrary/19877-machine-learning-ecmwf-roadmap-next-10-years


Technical Memo

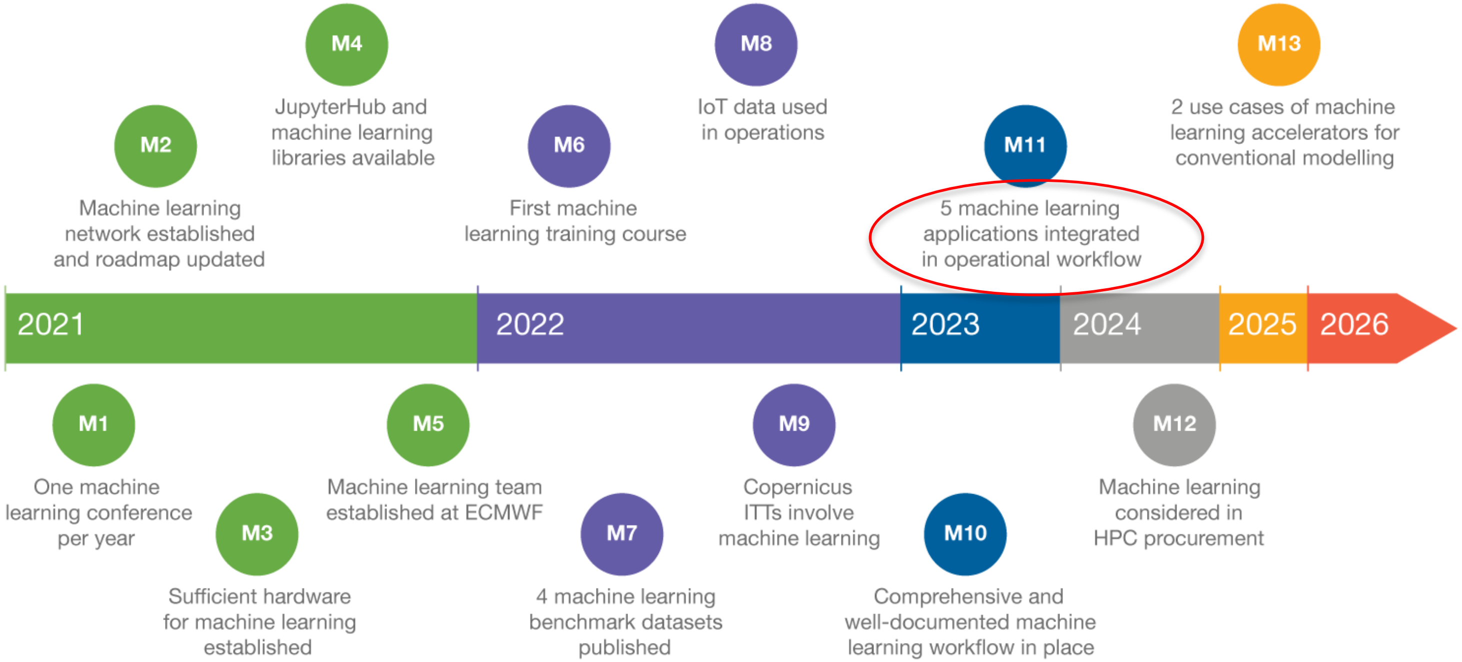
ECMWF
European Centre for Medium-Range Weather Forecasts

878

Machine learning at ECMWF: A roadmap for the next 10 years

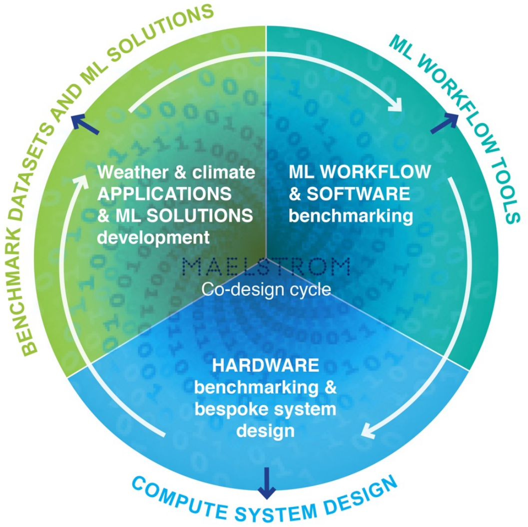
Peter Dueben, Umberto Modigliani, Alan Geer, Stephan Siemen, Florian Pappenberger, Peter Bauer, Andy Brown, Martin Palkovič, Baudouin Raoult, Nils Wedi, Vasileios Baousis

January 2021



Vision 2031

- It is difficult to distinguish between machine learning and domain sciences
- Data handling fully capable to serve machine learning needs
- Fully supported diagnostic tools via trustworthy AI
- Physical constraints can be represented in deep learning
- Use of machine learning as easy and normal as data re-gridding
- Unsupervised learning and causal discovery used on a regular basis
- Machine learning solutions from end-users integrated in workflow



MAELSTROM

Objective 1
Explore machine learning applications across the weather and climate prediction workflow and apply them to improve model efficiency and prediction quality.

Objective 2
Expand software and hardware infrastructure for machine learning.

Objective 3
Foster collaborations between domain and machine learning experts with the vision of merging the two communities.

Objective 4
Develop customised machine learning solutions for Earth system sciences that can be applied to various applications and at scale on current and future supercomputing infrastructure.

Objective 5
Train staff and Member and Co-operating State users and organise scientific meetings and workshops.

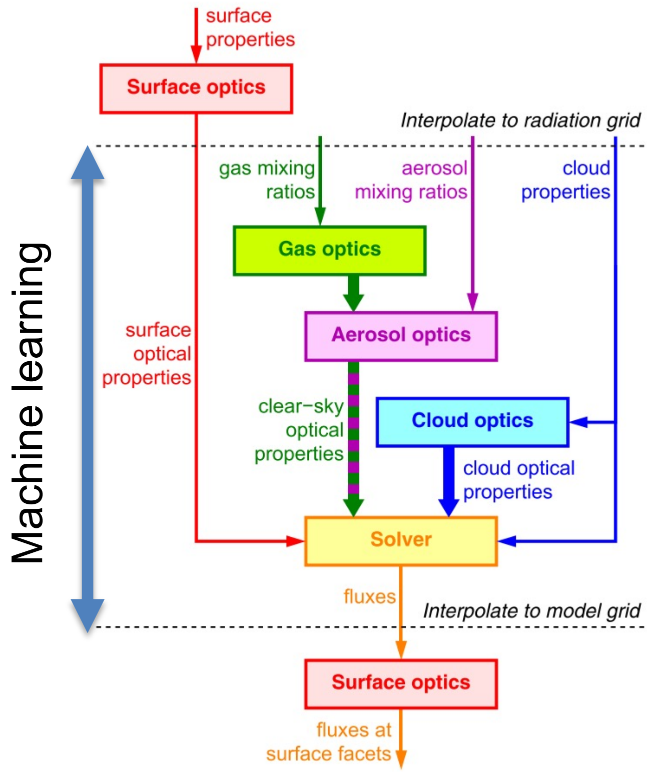
Hybrid NWP+ML

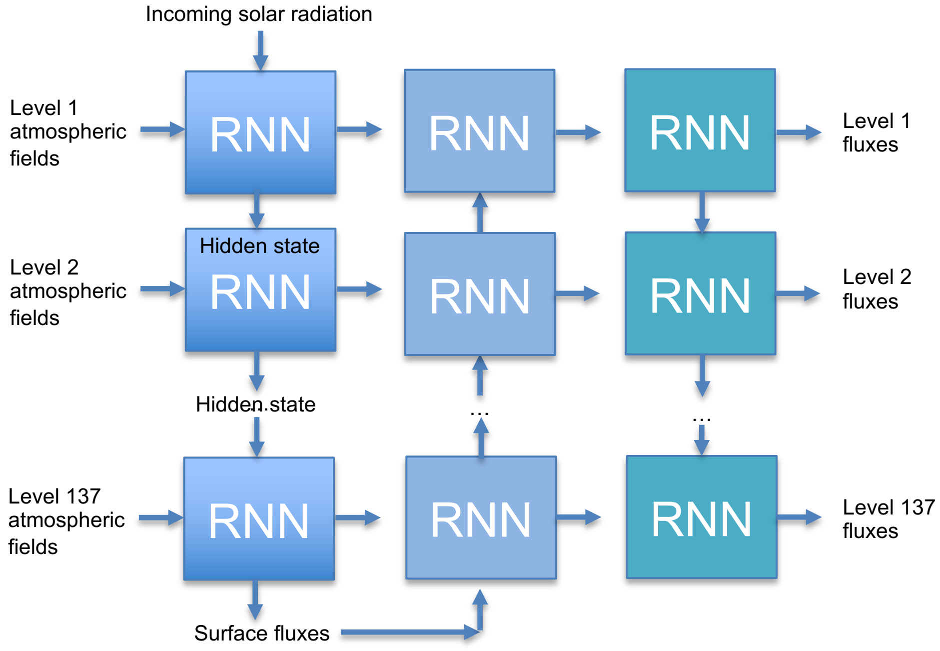
- Incremental approach to incorporating ML into existing NWP framework.
  - Augment existing model and tools.
- Many examples across the entire workflow.
  - Emulating model components for acceleration.
  - Observation operators.
  - Online learning of model bias within DA framework.
  - ML postprocessing.
  - Observation monitoring.
    - Mix of supervised and unsupervised learning to detect drift and other erroneous observations.
    - Operational in Q1.
- Good progress made, more to come…

Model component emulation

The radiation scheme is an expensive model component, being run at with a coarser timestep and spatial grid.

Can we accurately emulate the radiation scheme using neural networks?





Matthew Chantry, Robin Hogan, Peter Dueben @ ECMWF
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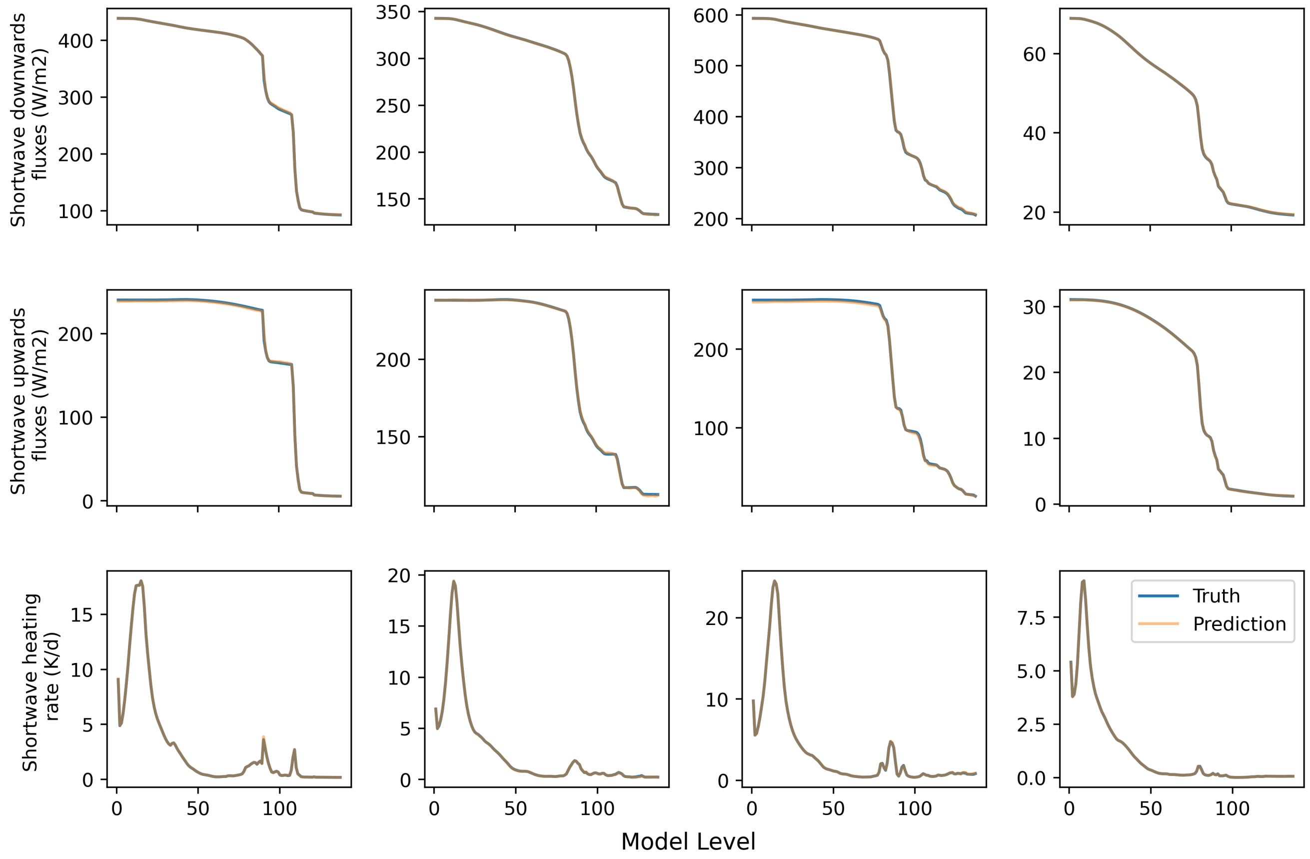
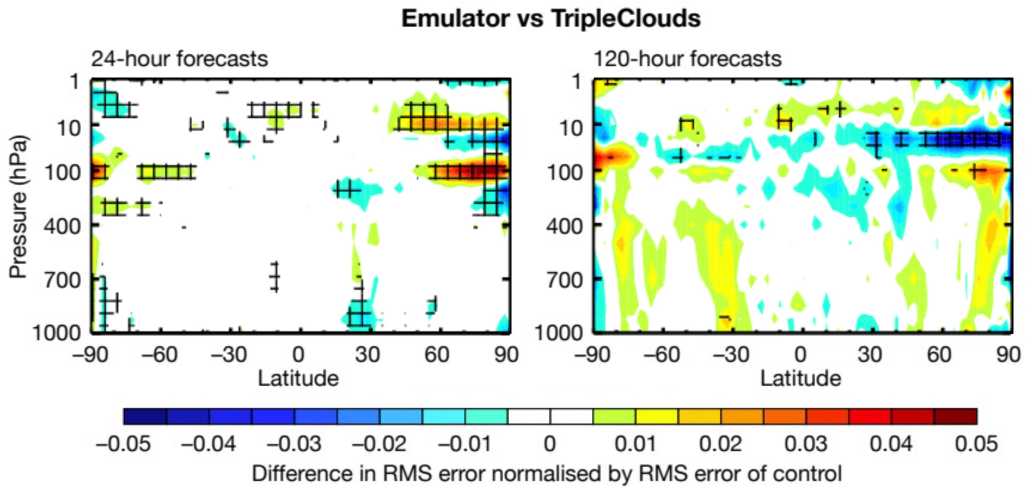


Example column predictions comparing existing scheme with neural network.



No degradations in forecast below 100hPa.
Faster than existing scheme decoupled from IFS.

Next steps: GPU use within IFS.

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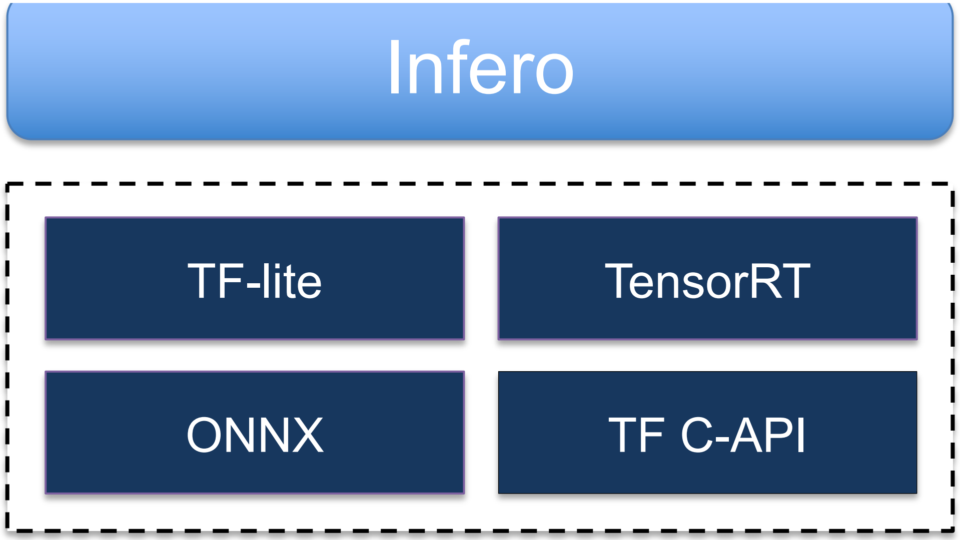
Infero library - A lower-level API for ML Inference in Operations

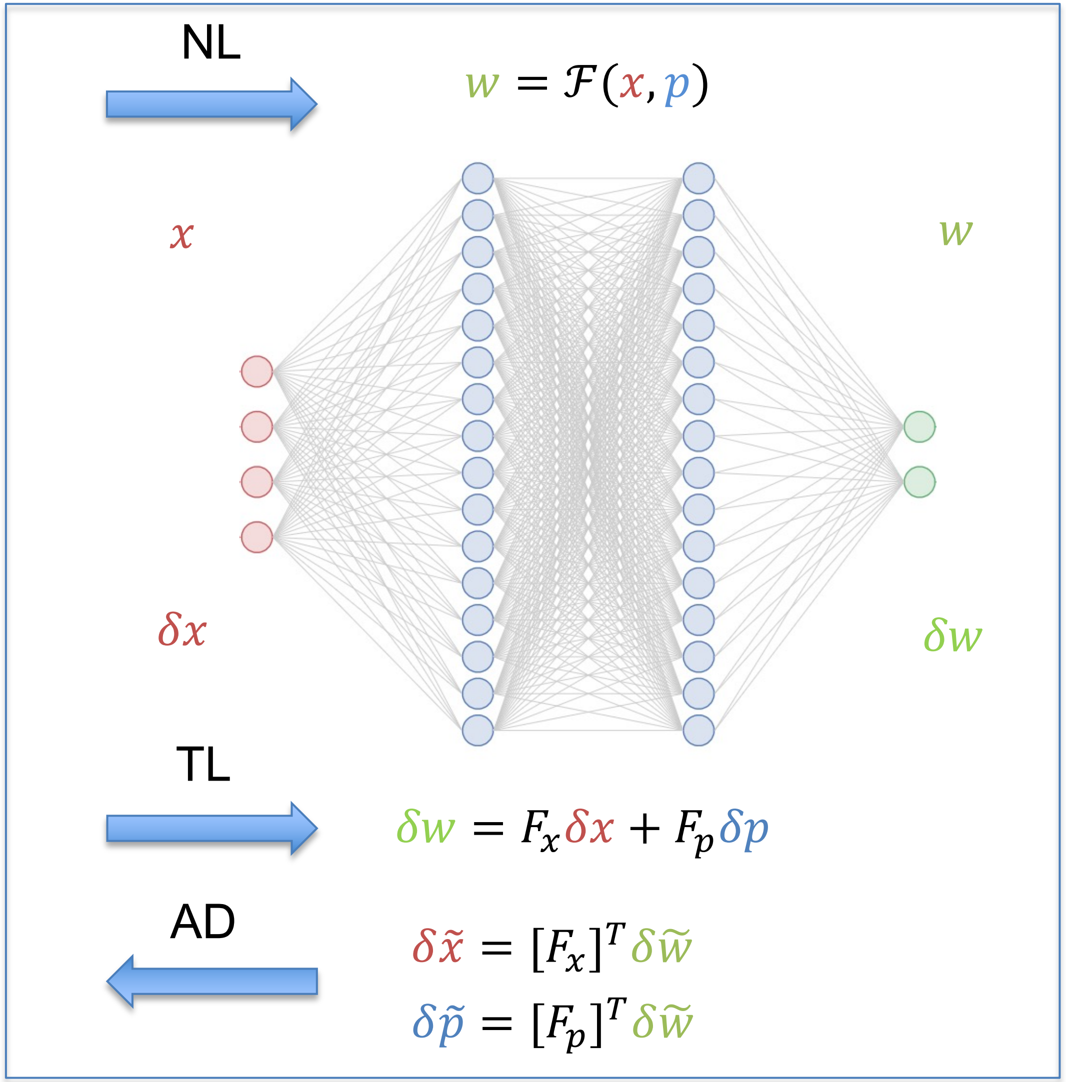
- One Interface, multiple backends
  - TF-lite
  - TensorRT
  - ONNX
  - TF C-API
- Infero provides API's:
  - C, C++, Fortran, Python
- Supports C and Fortran tensor
- Open-Source:
  - github.com/ecmwf-projects/infero

Fortran
```
model%initialise_from_yaml_file(yaml_path)
model%infer(input_tensor, output_tensor)
```

Python
```
model = pyinfero.Infero(model_path, model_type)
output = model.infer(input_tensor, output_shape)
```



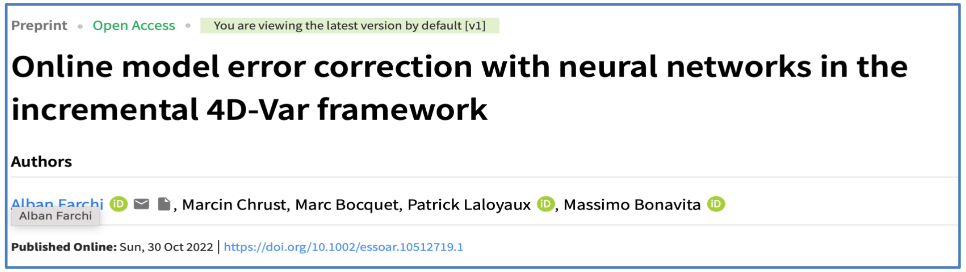
Towards online training of neural networks in the IFS 4D-Var



From offline, TensorFlow-based training of Neural Networks towards online learning within the ECMWF 4D-Var framework

FNN (Fortran Neural Network) **library**

- Fortran implementation of sequential Neural Networks equipped with tangent linear and adjoint operators required by incremental 4D-Var
- Tested for learning model error in a QG model (Farchi et al., 2022) and now implemented in the IFS.
- Potential applications: model error, observation bias, physics parametrizations, ..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Online model error correction with neural networks in the incremental 4D-Var framework

Authors

Alban Farchi, Marcin Chrust, Marc Bocquet, Patrick Laloyaux, Massimo Bonavita

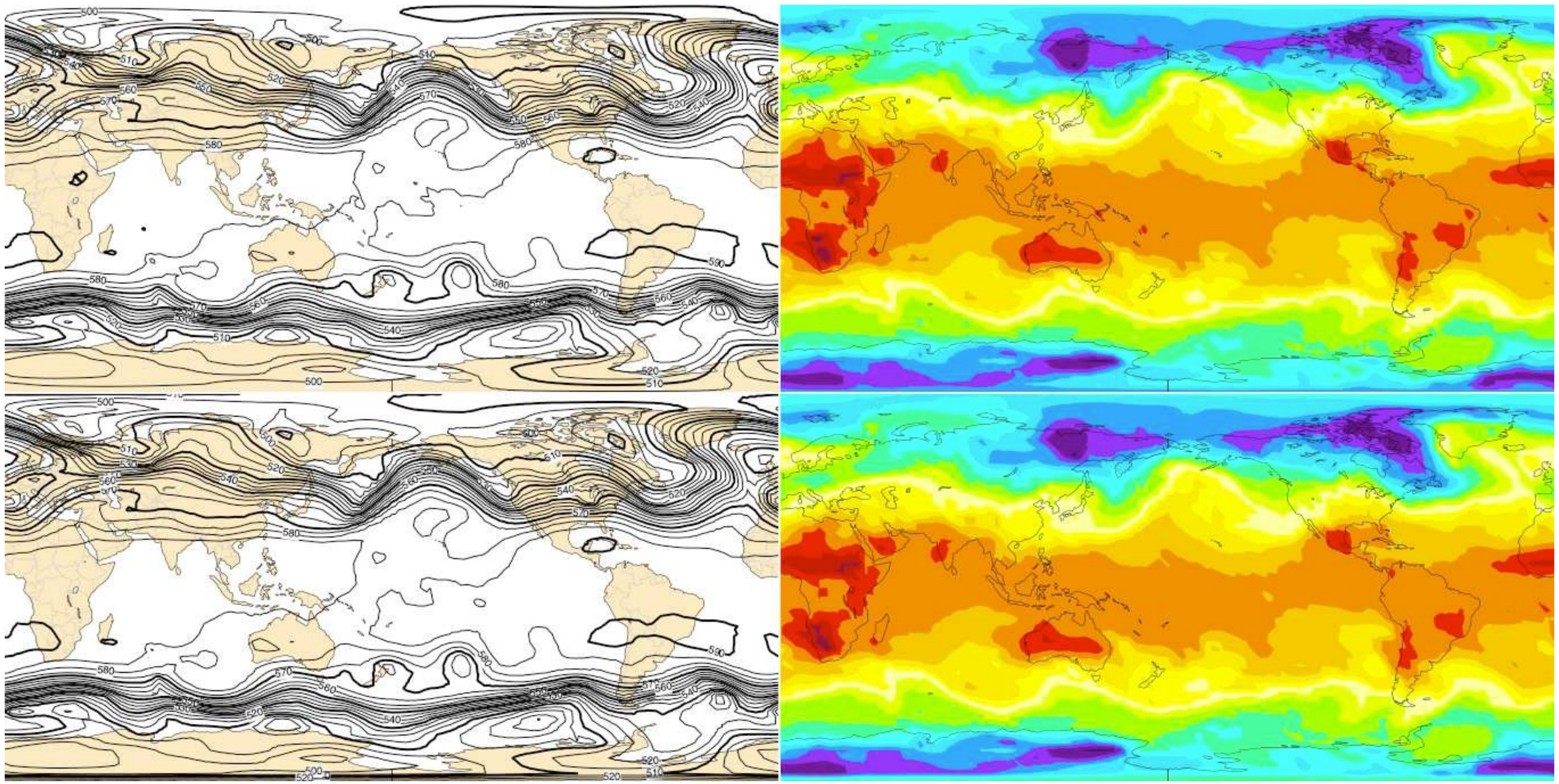
Published Online: Sun, 30 Oct 2022 | https://doi.org/10.1002/essoar.10512719.1

However…

landscape has changed in 2 years

IFS

z500



t850

Pangu-Weather

ECMWF

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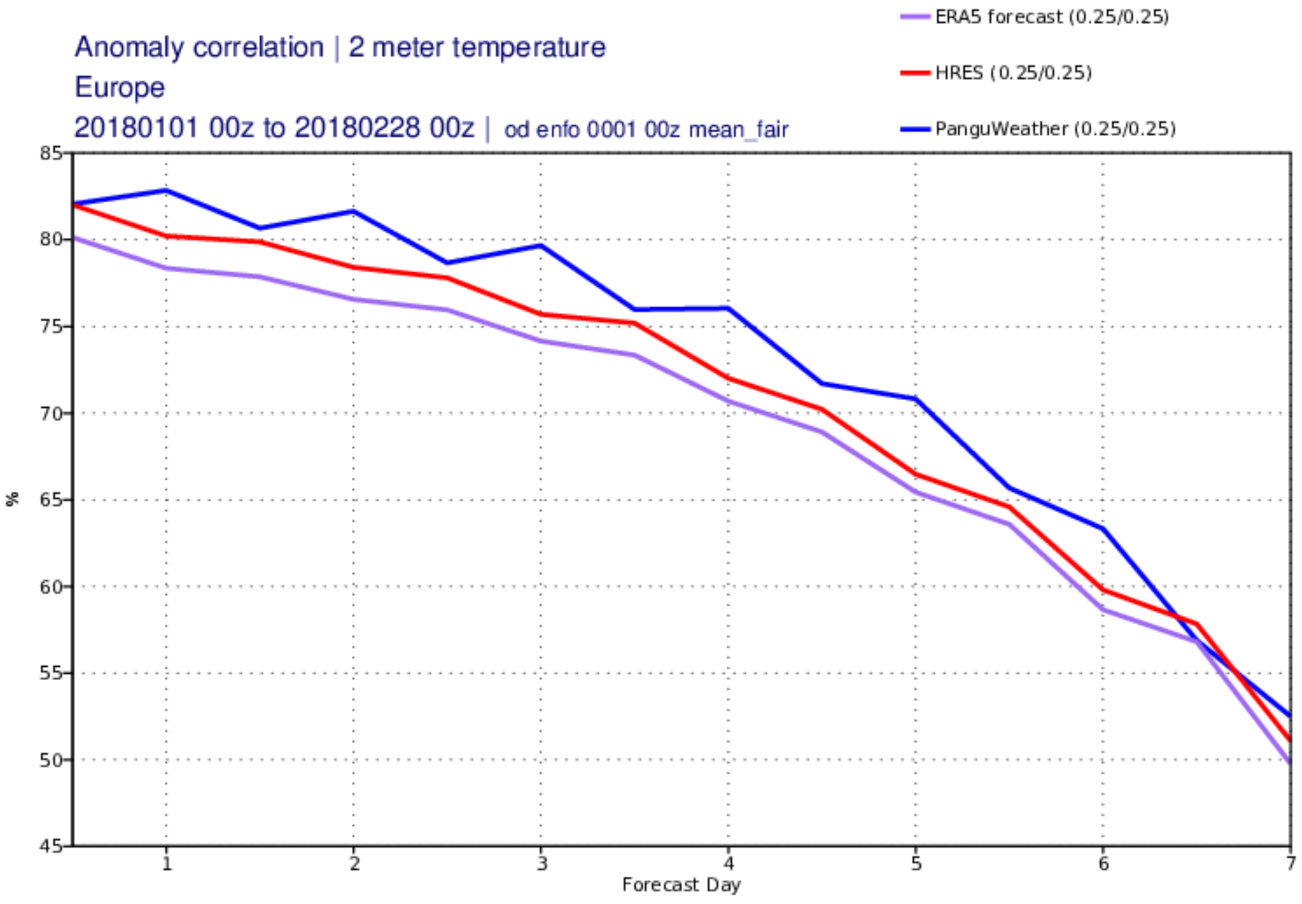
ECMWF assessment of data-driven models

Assessing Pangu-Weather against SYNOP observations.

- Still skilful when verified against independent dataset.

- For some variables it beats HRES and ERA5 forecasts at 0.25°.

- Pangu model now public, we have it running at ECMWF for further evaluation.



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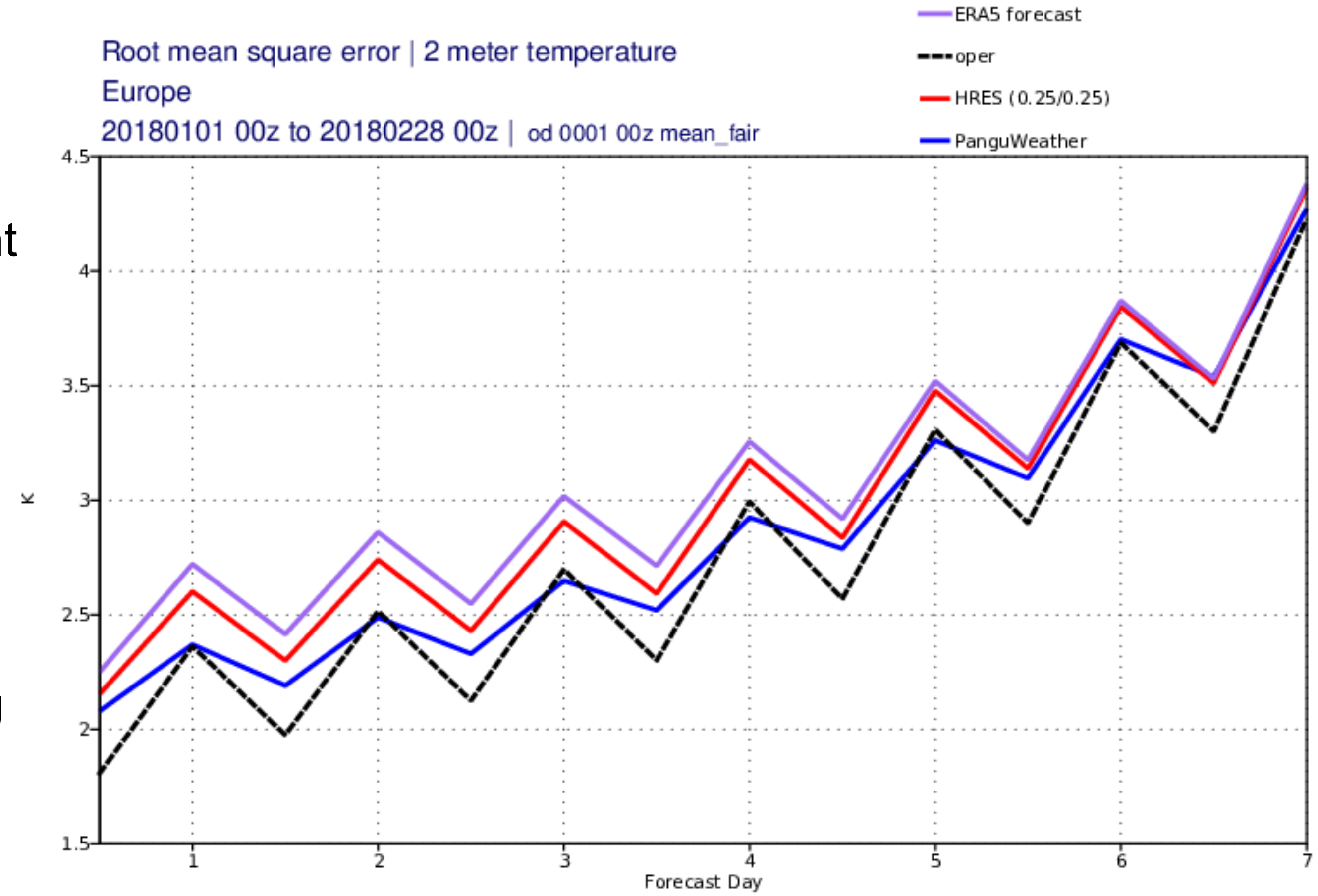
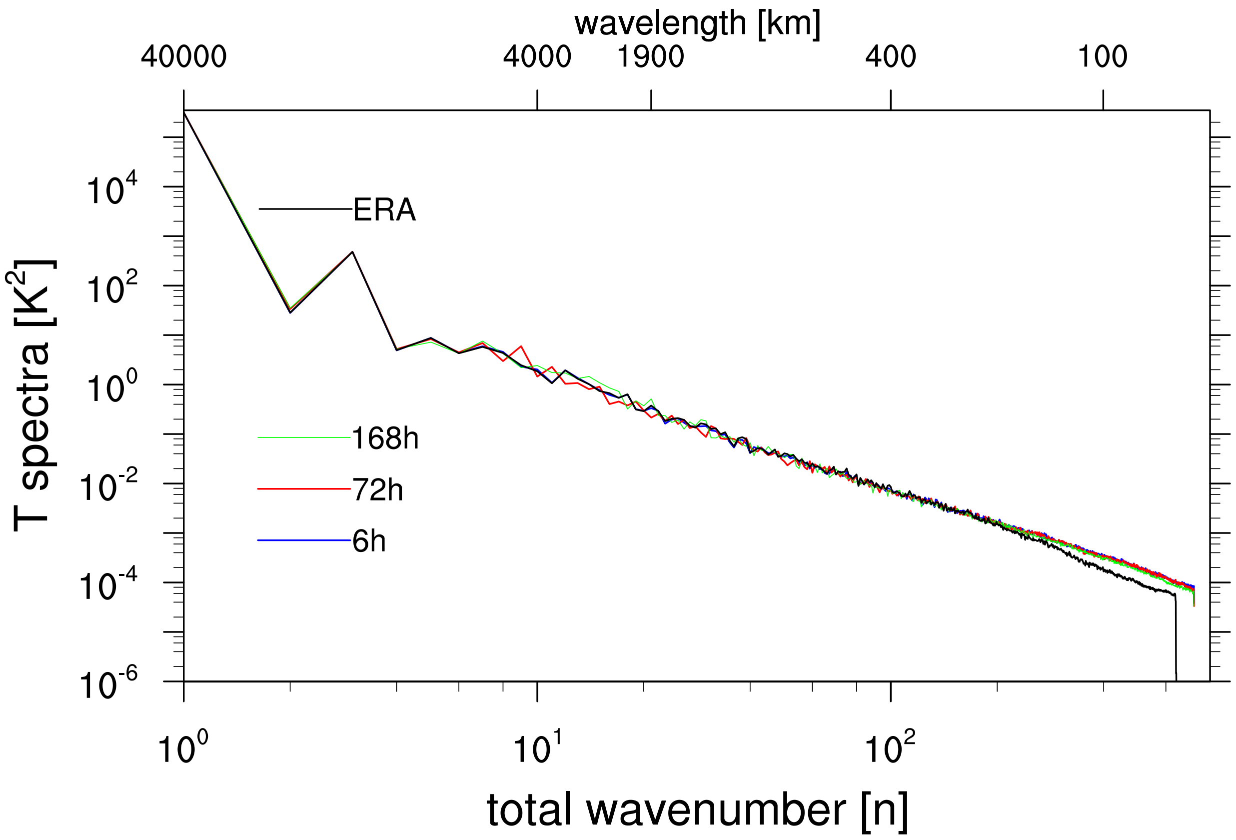
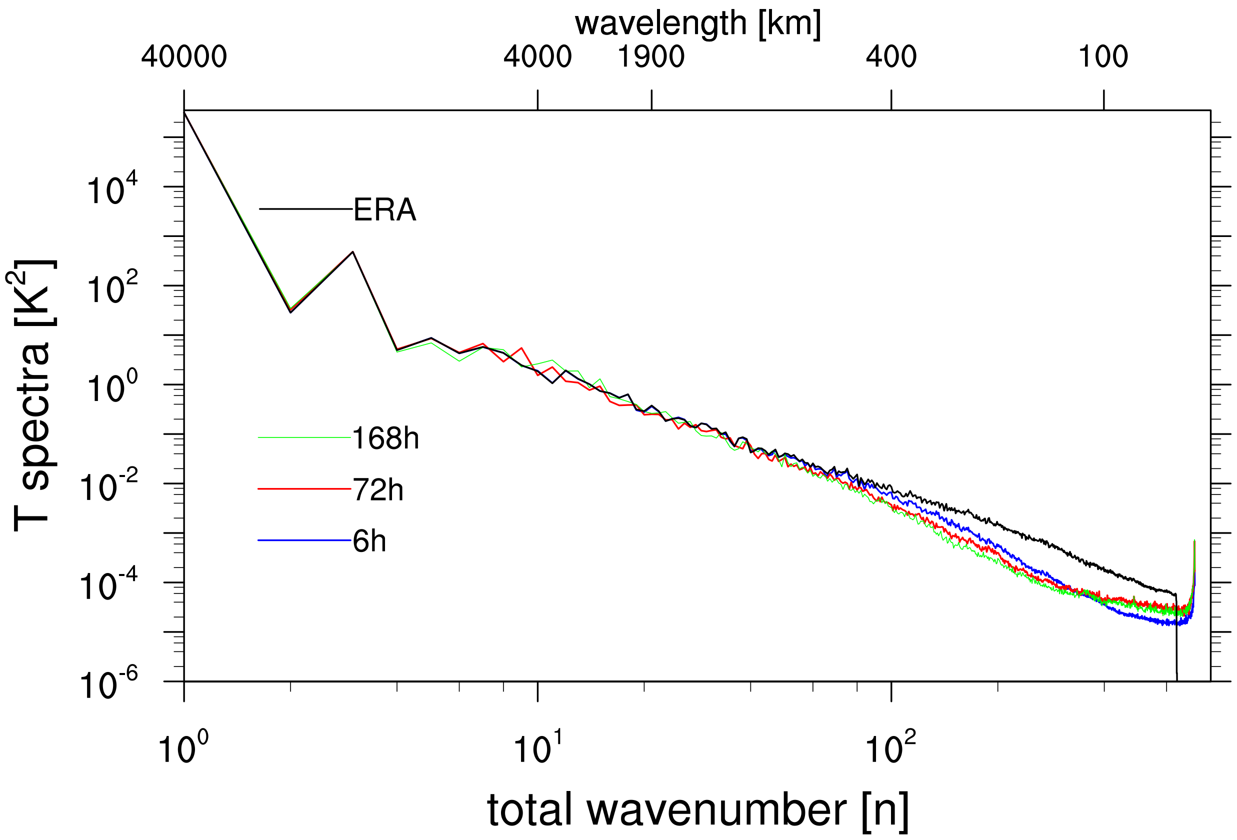


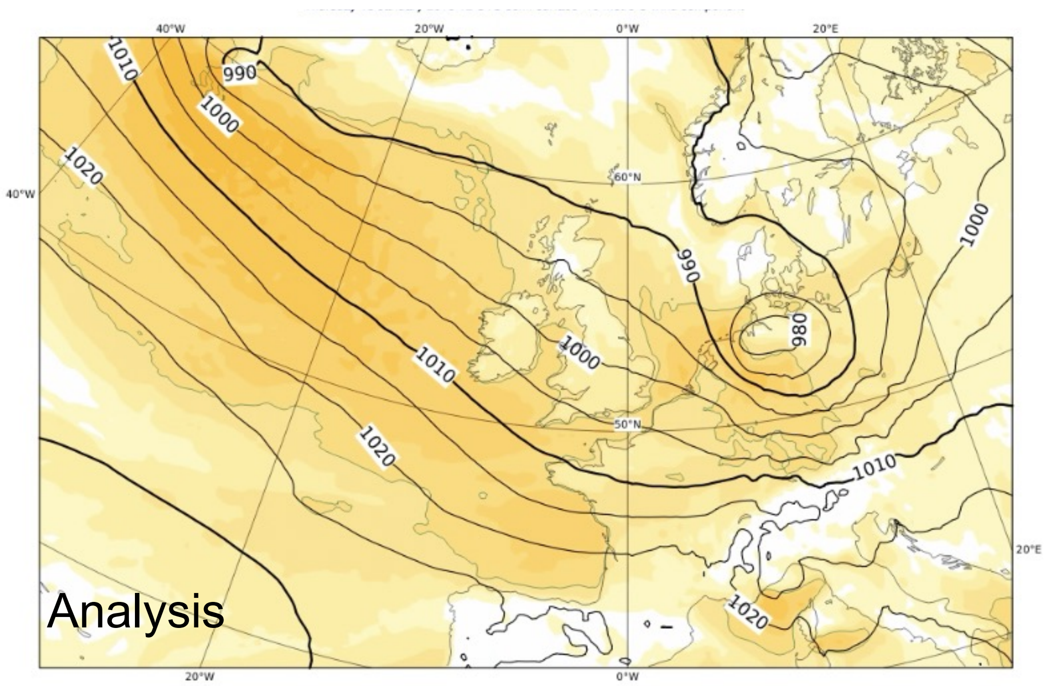
ECMWF assessment of data-driven models

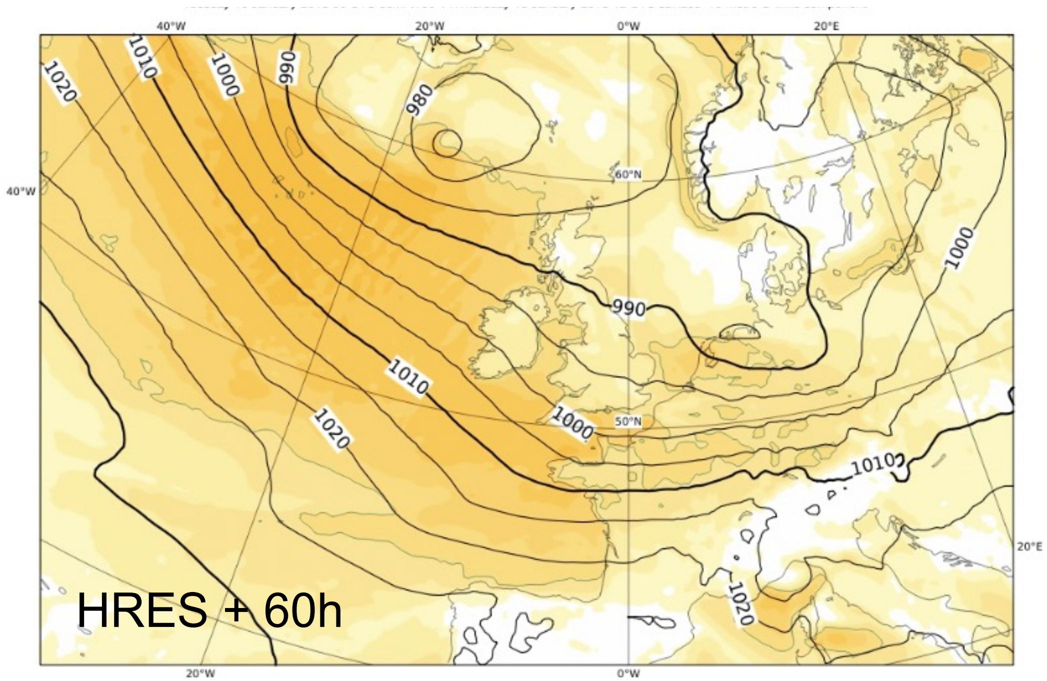
HRES T850



Pangu T850

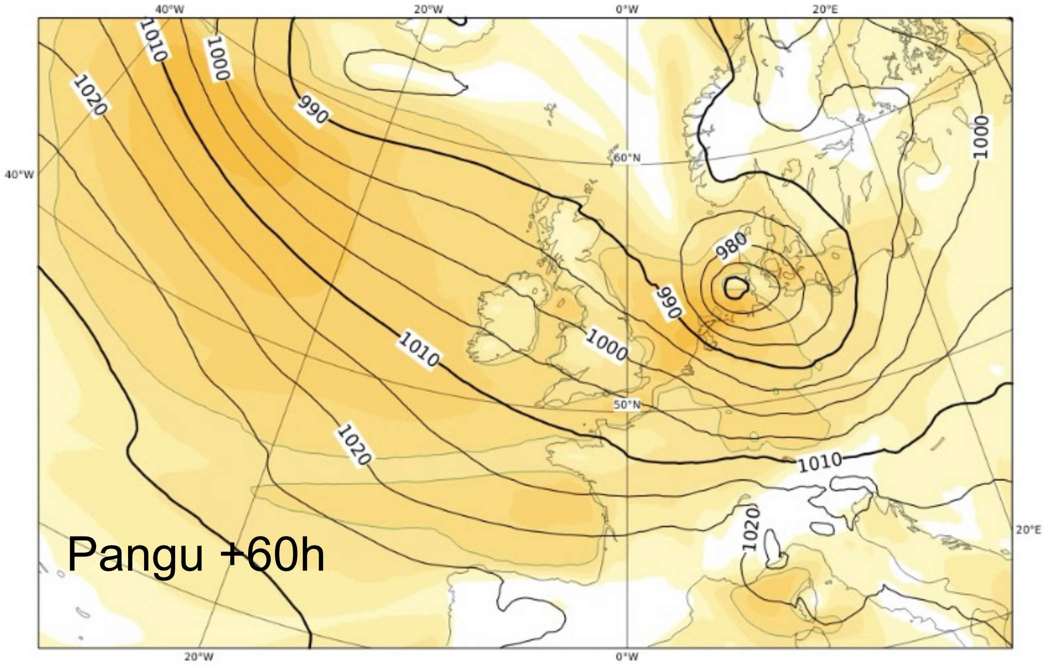






Case study: Windstorm
Friederike 18 January 2018

Contours of surface pressure, colour map wind speed.



A new forecast tool?

Strengths

- Models can run in seconds on single GPUs.
- Only a sparse representation of model state required (e.g. only O(10) vertical levels).

Weaknesses

- Unclear evaluation for humidity/precipitation.
- Blurring/damping at longer lead times minimises MSE but may impact value.
- If a complete state of the atmosphere is required this will undercut computational advantages.

Existing results do not incorporate much domain knowledge, room to add value.

Three possible futures?

1. Hybrid NWP+ML.
   – Already delivering improvements.

2. Data-driven model trained from analysis, providing giant ensembles at a fraction of the cost.
   – Convential NWP (or hybrid) provides initial conditions.

3. Data-driven model trained from observations…

- Not equally likely destinations.
- But now is the time to explore.