AI for Climate Modelling

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THE ROYAL SOCIETY

ECMWF | EUROPEAN CENTRE FOR MEDIUM-RANGE WEATHER FORECASTS

summit

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The strength of a common goal

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

Funded by the European Union

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Why would machine learning help in climate modelling?

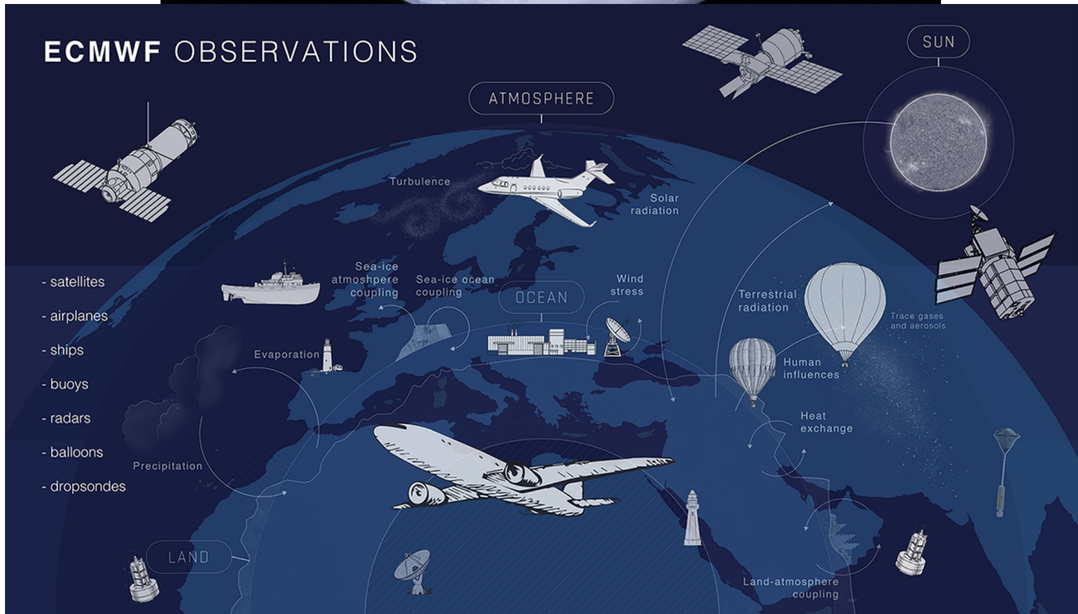
Predictions of weather and climate are difficult:

- The Earth is huge, resolution is limited and we cannot represent all important processes within model simulations
- The Earth System shows “chaotic” dynamics which makes it difficult to predict the future based on equations
- All Earth System components (atmosphere, ocean, land surface, cloud physics,…) are connected in a non-trivial way
- Some of the processes involved are not well understood

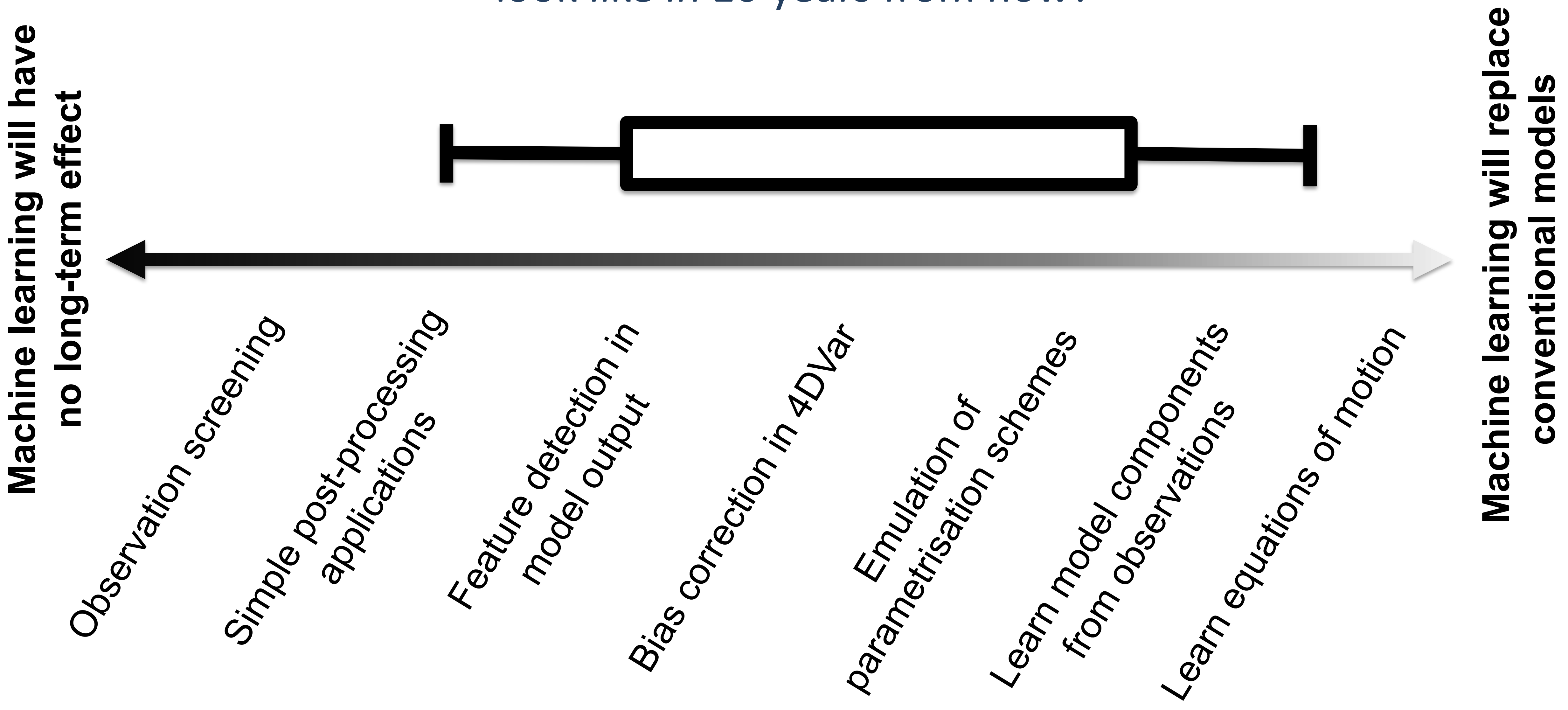
However, we have hundreds of petabytes of Earth System observation and model data available

➢ **Modern machine learning tools allow to learn the behaviour of very complex non-linear systems from data.**

➢ **There are many application areas for machine learning in weather and climate modelling**



What will machine learning for numerical weather predictions look like in 10 years from now?



The uncertainty range is still very large...

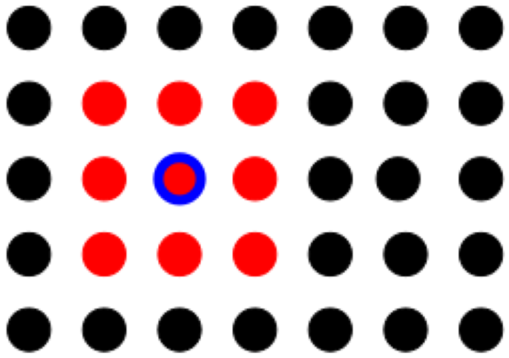
Can we replace conventional Earth System models by deep learning?

We could base the entire model on neural networks and trash the conventional models.?
There are limitations for existing models and ECMWF provides access to hundreds of petabytes of data

A simple test configuration:

- We retrieve historical data (ERA5) for geopotential at 500 hPa (Z500) for the last decades (>65,000 global data sets)
- We map the global data to a coarse two-dimensional grid (60x31)
- We learn to predict the update of the field from one hour to the next using deep learning
- Once we have learned the update, we can perform predictions into the future

No physical understanding is required!



Dueben and Bauer GMD 2018

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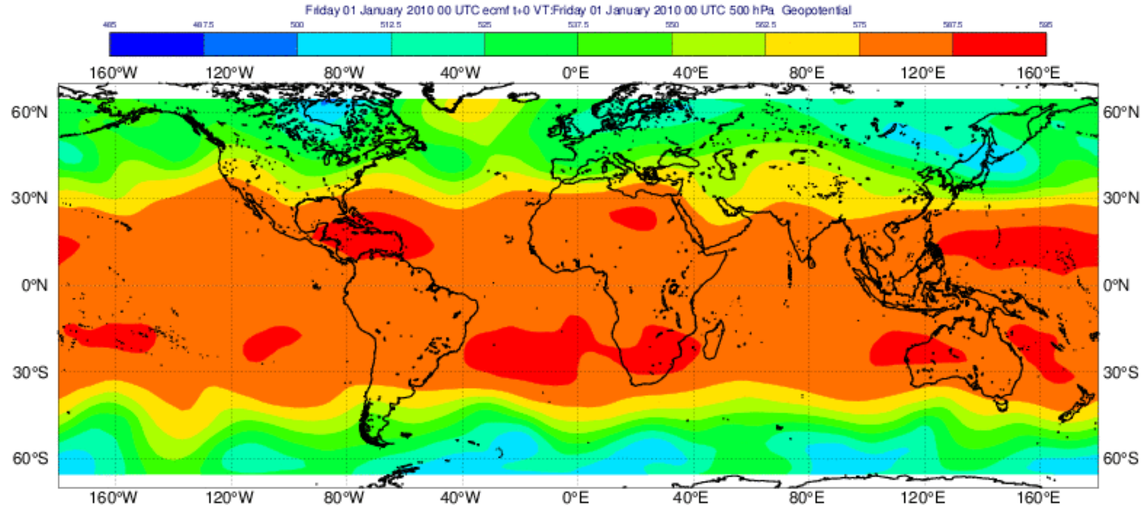
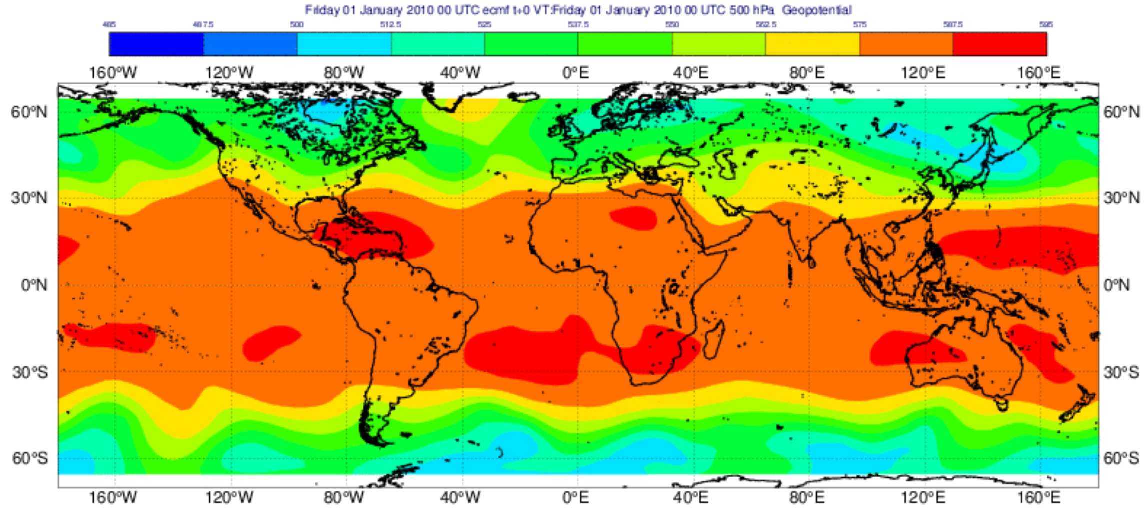




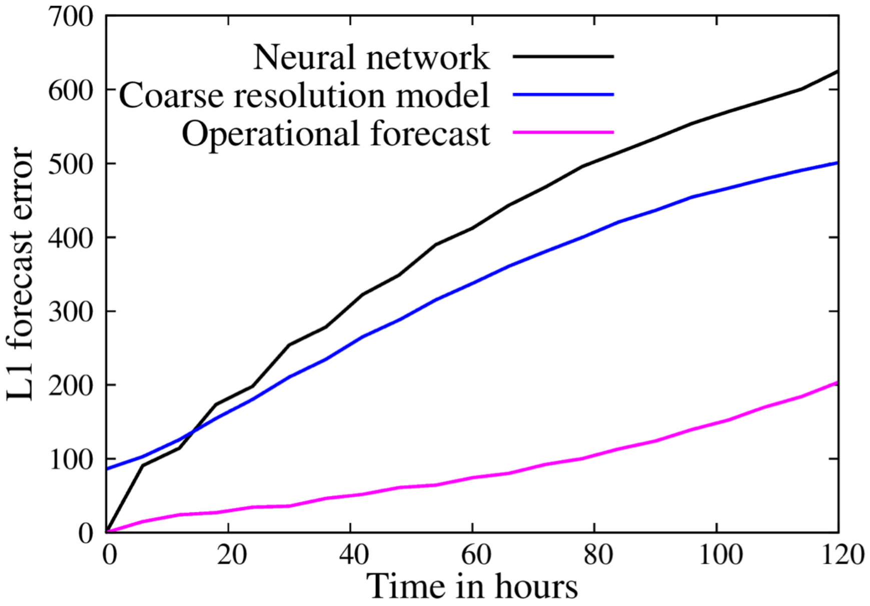
Time evolution of Z500 for historic data and a neural network prediction.
Can you tell which one is the neural network?

- The neural network is picking up the dynamics nicely.
- Forecast errors are comparable if we compare like with like.
- Is this the future?

Unlikely…

- The simulations are unstable and it is unclear how to fix conservation properties.
- It is unknown how to increase complexity and how to fix feature interactions.
- There are only ~40 years of data available.

However, there is a lot of progress at the moment:
Scher and Messori GMD 2019; Weyn, Durran, and Caruana JAMES 2019; …



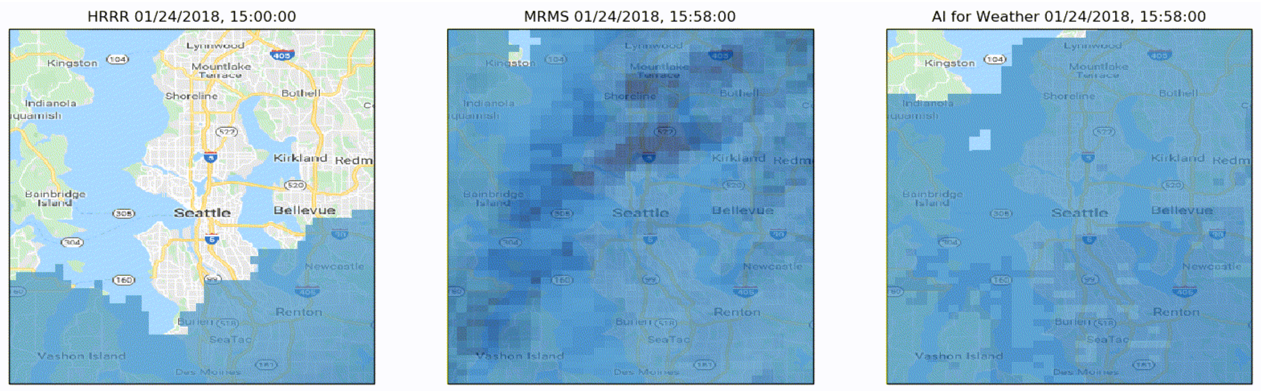
Dueben and Bauer GMD 2018

Can we replace conventional Earth System models by deep learning?

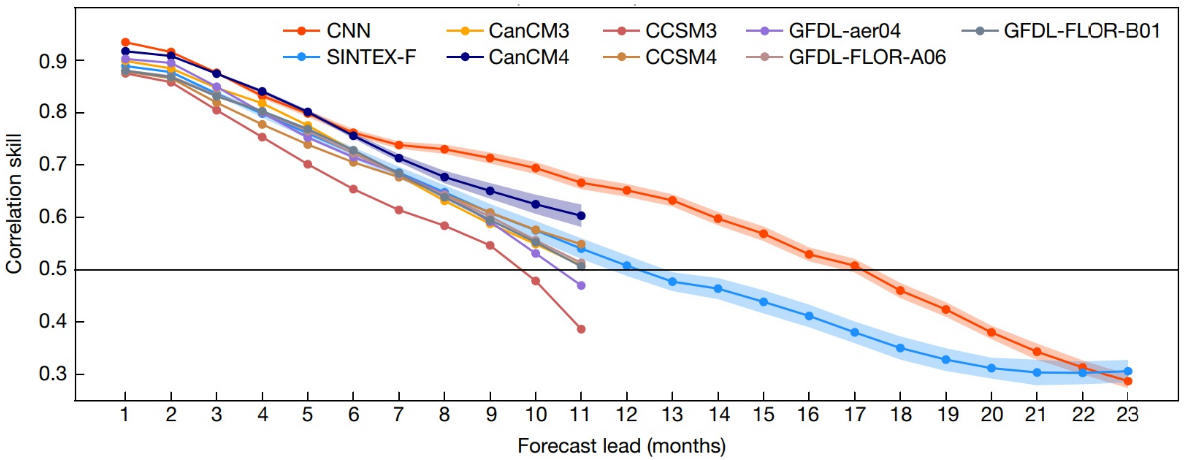
However, machine learning models are very promising for **now-casting applications or seasonal/multi-year predictions.**

1-hour precipitation predictions by Google: Agrawal, Barrington, Bromberg, Burge, Gazen, Hickey arXiv:1912.12132

NOAA forecast | Ground truth | Machine learning:



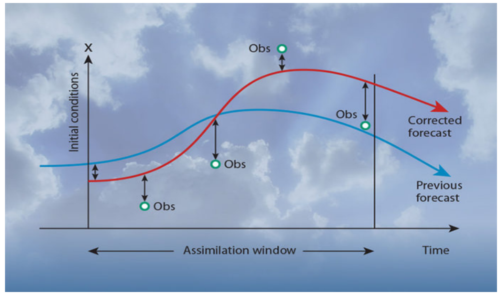
Deep learning for multi-year ENSO forecasts: Ham, Kim, Luo *Nature* 2019



Climate?

Machine learning applications across the numerical weather prediction workflow

Observations → **Data-assimilation** → **Numerical weather forecasts** → **Post-processing and dissemination**



Application areas for machine learning are spread over the entire workflow:

weather data monitoring, real-time quality control for observational data, anomaly interpretation, guided quality assignment and decision making, data fusion from different sources, correction of observation error,

learn governing differential equations, non-linear bias correction, learn operational operators, define optical properties of hydrometeors and aerosols, emulate conventional tools to improve efficiency,

emulate model components, develop improved parametrisation schemes, build better error models, learn the underlying equations of motion, generate tangent linear or adjoint code from machine learning emulators,

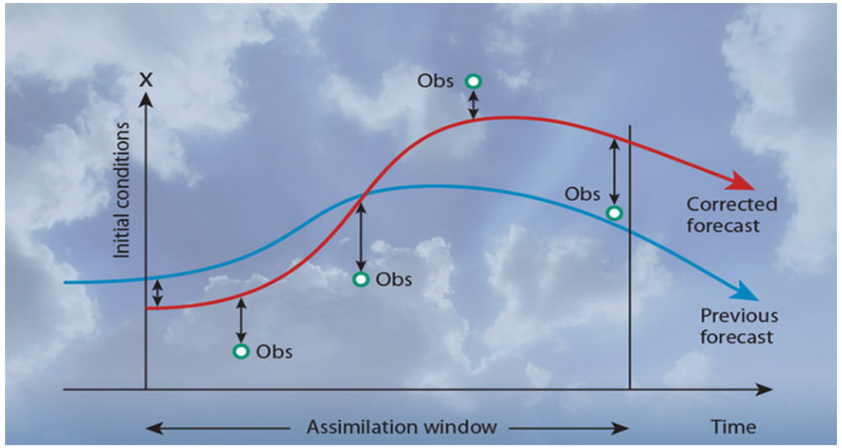
real-time adjustments of forecast products, feature detection, uncertainty quantification, error corrections for seasonal predictions, development of low-complexity models, bespoke products for business opportunities,

and many more…

I will present a couple of example applications in the following.

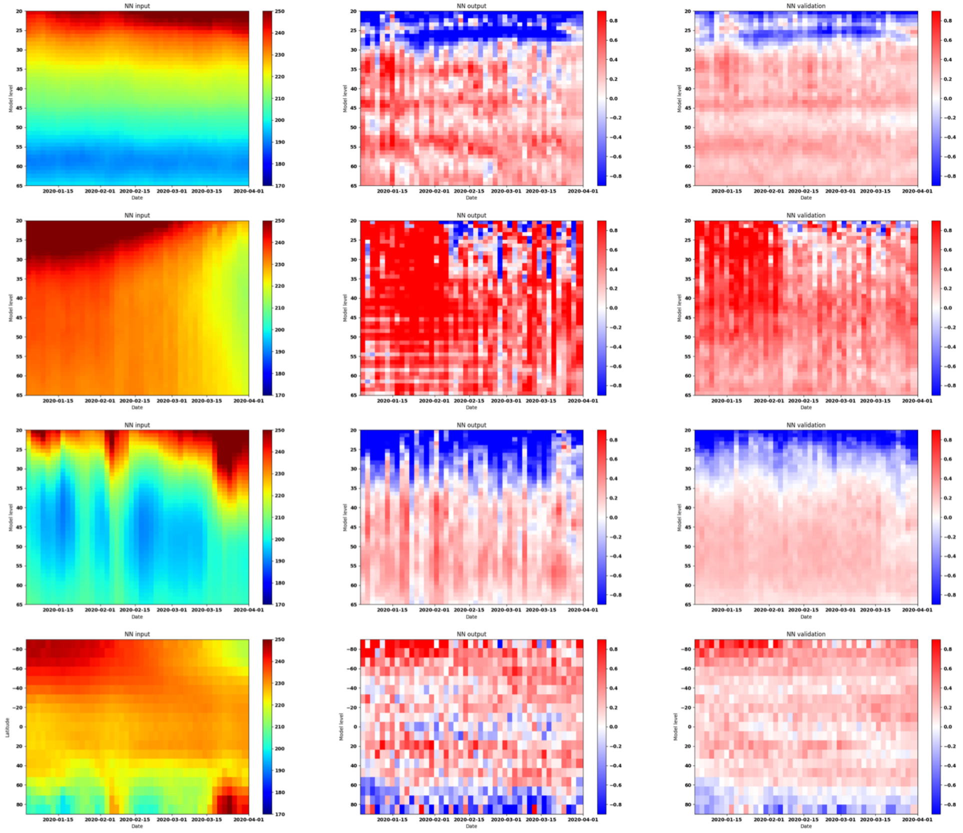
Example 1: Data assimilation: Bias-correct the forecast model in 4DVar data assimilation

- Data-assimilation blends observations and the forecast model to generate initial conditions for weather predictions
- During data-assimilation the model trajectory is “synchronised” with observations for the same weather regimes
- It is possible to learn model error when comparing the model with (trustworthy) observations



Two approaches:

- Learn model error within the 4DVar data-assimilation framework for so-called “weak-constraint 4D-Var”
- Learn model error from a direct comparison of the model trajectory to observations or analysis increments using deep learning. This can be done with a column-based approach or with three-dimensional machine learning solutions



Benefit:

When the bias is learned, it can be used to:

- Correct for the bias during data-assimilation to improve initial conditions
- Correct for the bias in forecast simulations to improve predictions (discussed controversially)
- Understand model deficiencies

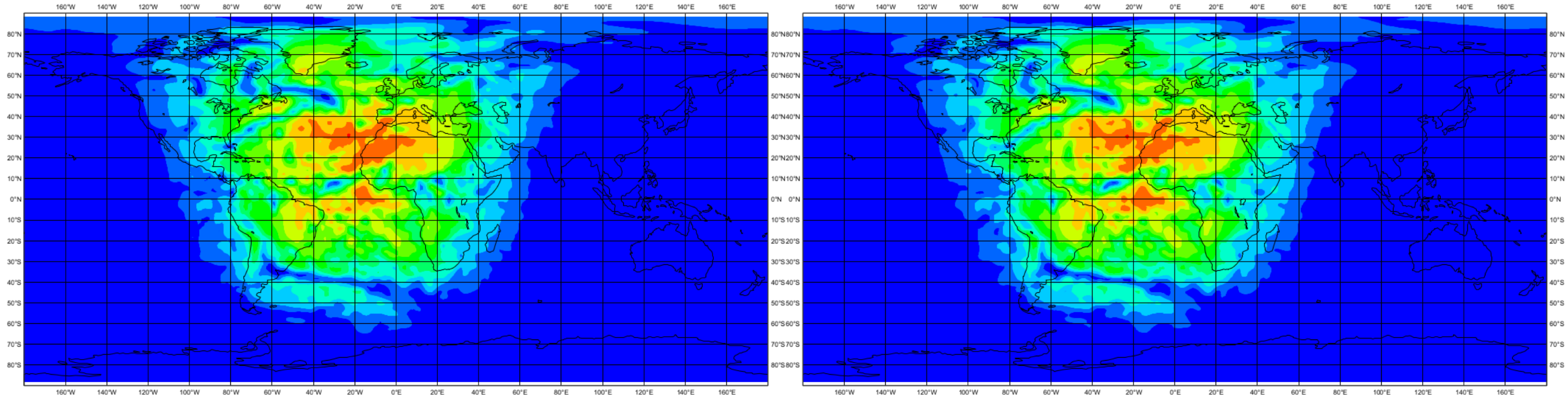
Laloyaux, Bonavita and Dueben @ ECMWF + Kurth and Hall @ NVIDIA

Example 2: Numerical weather forecasts: To emulate the radiation scheme

- Store input/output data pairs of the radiation schemes
- Use this data to train a neural network
- Replace the radiation scheme by the neural network within the model

This is a very active area of research:
Rasp, Pritchard, Gentine PNAS 2018
Brenowitz and Bretherton GRL 2018
…

Why would you do this?
Neural networks are likely to be much more efficient and portable to heterogenous hardware



Surface downward solar radiation for the original scheme and the neural network emulator (based on a ResNet).

The approach is working and the neural network is ~10 times faster than the original scheme.
However, model results are still degraded.

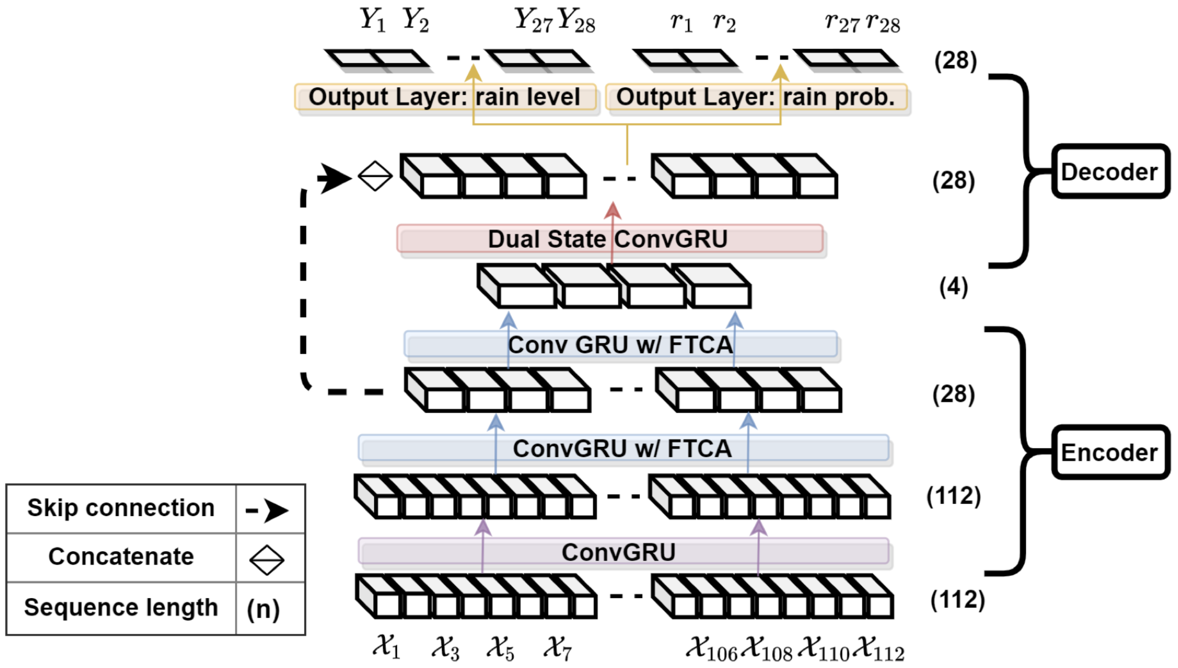
Dueben, Hogan, Bauer @ECMWF and Progsch, Angerer @NVIDIA

Example 3: Post-processing and dissemination: Precipitation down-scaling

Problem: Learn to map precipitation predictions from ERA5 reanalysis data at ~50 km resolution to E-OBS local precipitation observations at ~10 km resolution over the UK.

Use case: Eventually, apply the tool to climate predictions to understand changes of local precipitation pattern due to climate change.

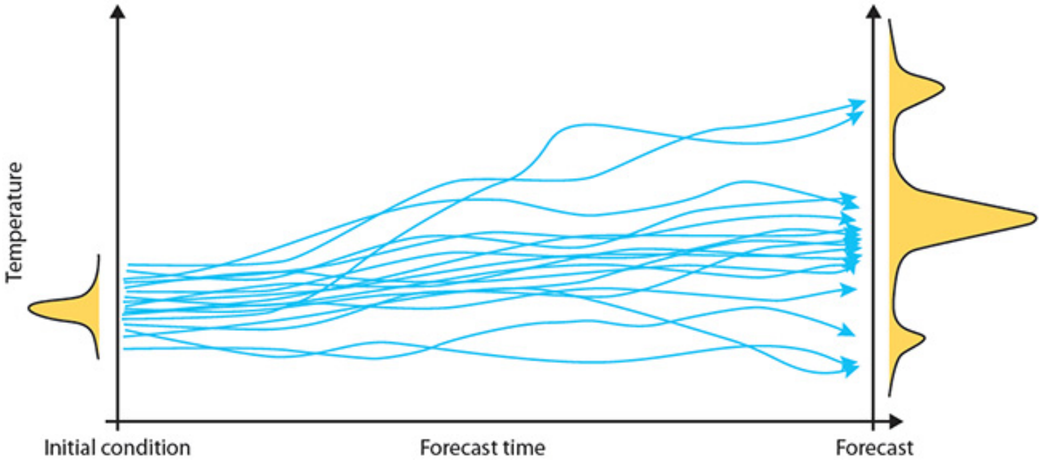
Method: Use Tru-NET with a mixture of ConvGru layers to represent spatial-temporal scale interactions and a novel Fused Temporal Cross Attention mechanism to improve time dependencies.

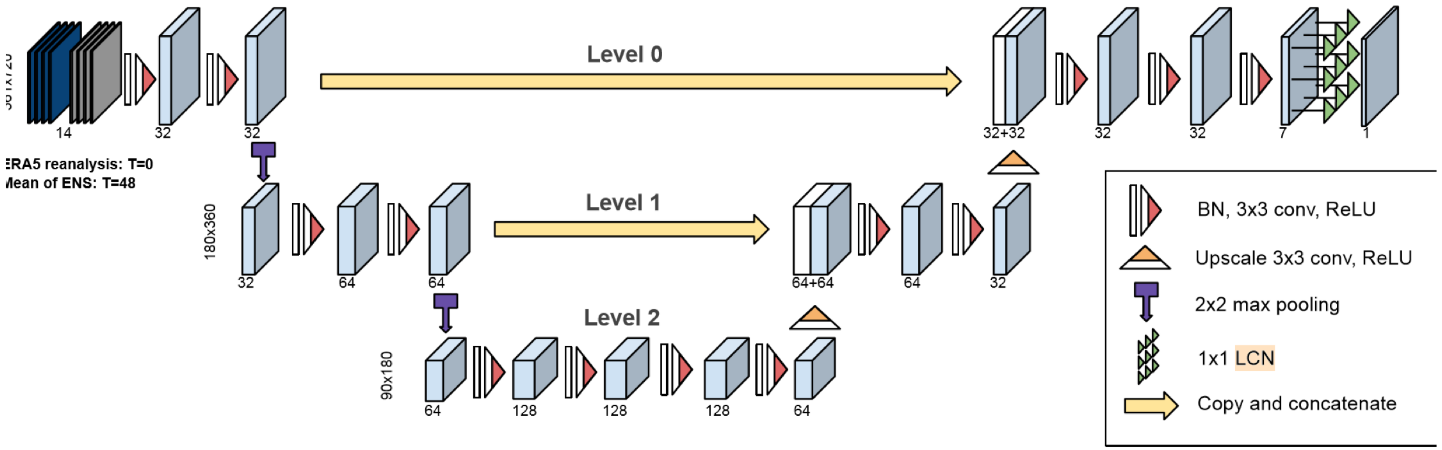


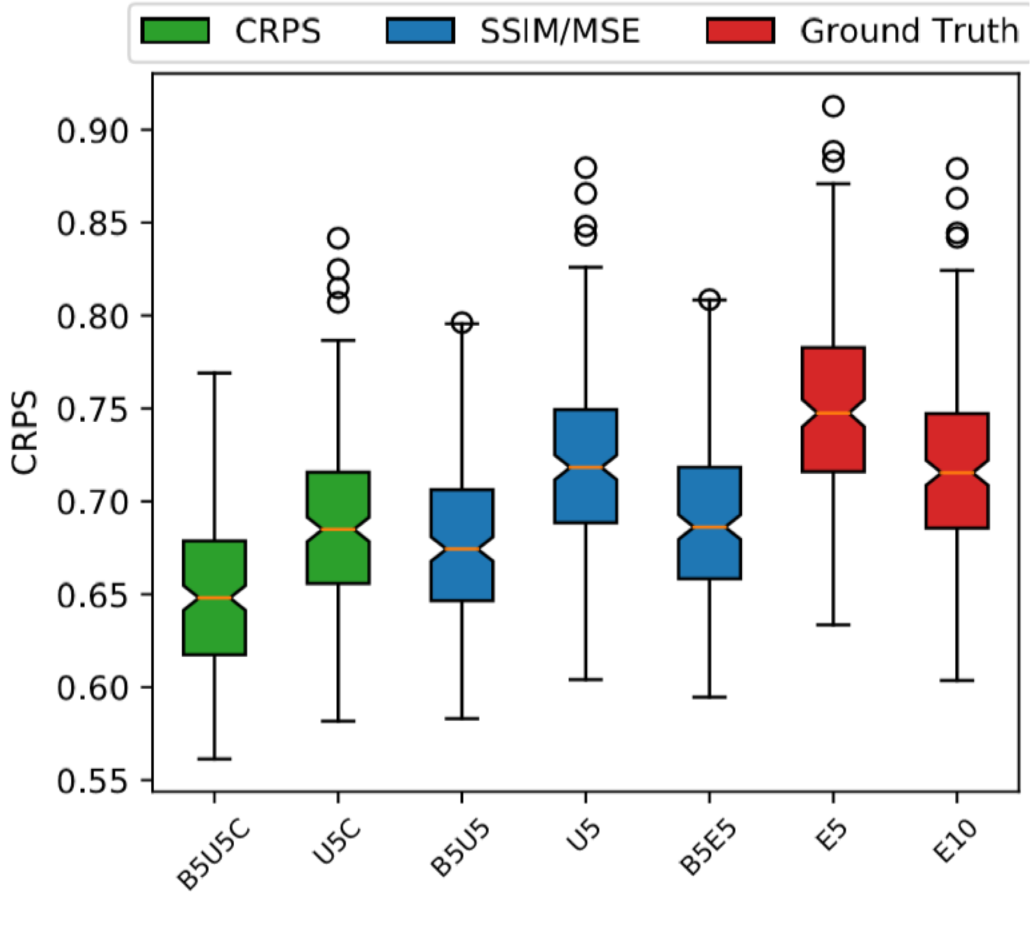
Model	RMSE
IFS within ERA5	3.627
Tru-Net	3.005

Adewoyin, Dueben, Watson, He, Dutta http://arxiv.org/abs/2008.09090

Example 4: Ensemble post-processing







(a) T850

Ensemble predictions are important but expensive.

Can we improve ensemble skill scores from a small number of ensemble members via deep learning?

- Use global fields of five ensemble members as inputs.
- Correct the ensemble scores of temperature at 850 hPa and Z500 hPa for a 2-day forecast towards a full 10 member ensemble forecast.

Grönquist, Yao, Ben-Nun, Dryden, Dueben, Lavarini, Li, Hoefler https://arxiv.org/abs/2005.08748

Scientific challenges for machine learning in numerical weather predictions

There is no fundamental reason not to use a black box within weather and climate models but there are unanswered questions.

- Can we use our knowledge about the Earth System to improve machine learning tools?
- Can we diagnose physical knowledge from the machine learning tools?
- Can we remove errors from neural networks and secure conservation laws?
- Can we guarantee reproducibility?
- Can we find the optimal hyper-parameters?
- Can we efficiently scale machine learning tools to high performance computing applications?
- Can we interface machine learning tools with conventional models?
- Can we design good training data (short time steps and high resolution, labelled datasets)?
- Can we explore the full phase space (all weather regimes) during training?

Many scientists are working on these challenges as we speak.

Conclusions

- There are a large number of application areas throughout the prediction workflow in weather and climate modelling for which machine learning could really make a difference.

- The weather and climate community is still only at the beginning to explore the potential of machine learning (and in particular deep learning).

- There are challenges for the application of black-box machine learning solutions within weather and climate models that need to be addressed.

- There is still a lot of work to be done regarding the development of customised machine learning solutions for weather and climate predictions.

Many thanks!

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Some room for interactions with machine learning efforts at ECMWF

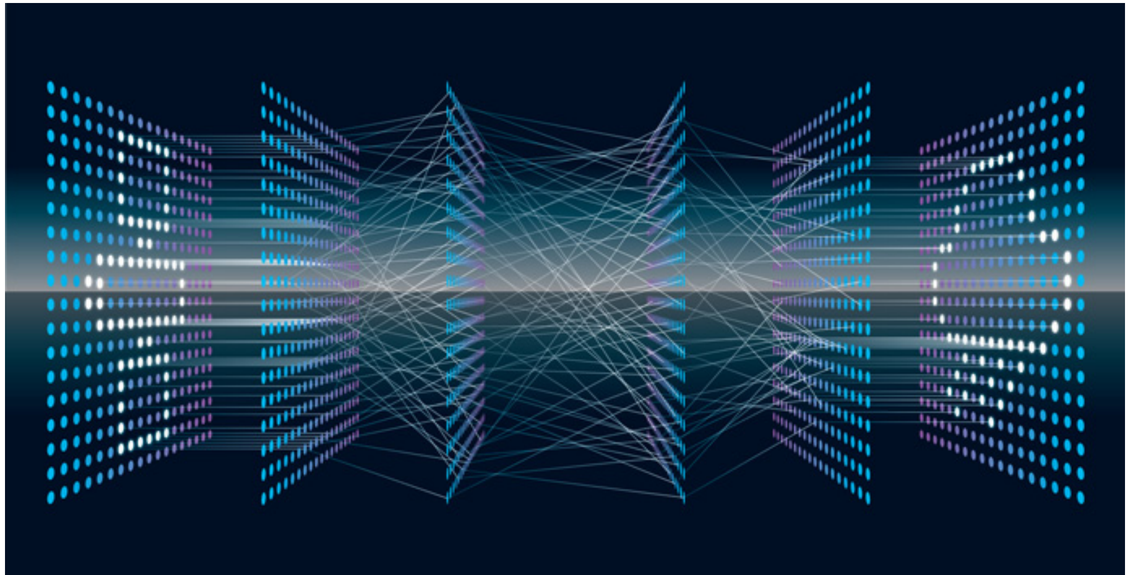
ECMWF-ESA Workshop on Machine Learning for Earth System Observation and Prediction at ECMWF 5-8 October 2020. More information is here.

We have also started a special seminar series on Machine Learning that is broadcasted.

ECMWF is developing the European Weather Cloud in collaboration with EUMETSAT.

Our MAELSTROM EuroHPC proposal was successful which will allow us to develop customised machine learning solutions for weather and climate models.

We are hiring soon.



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