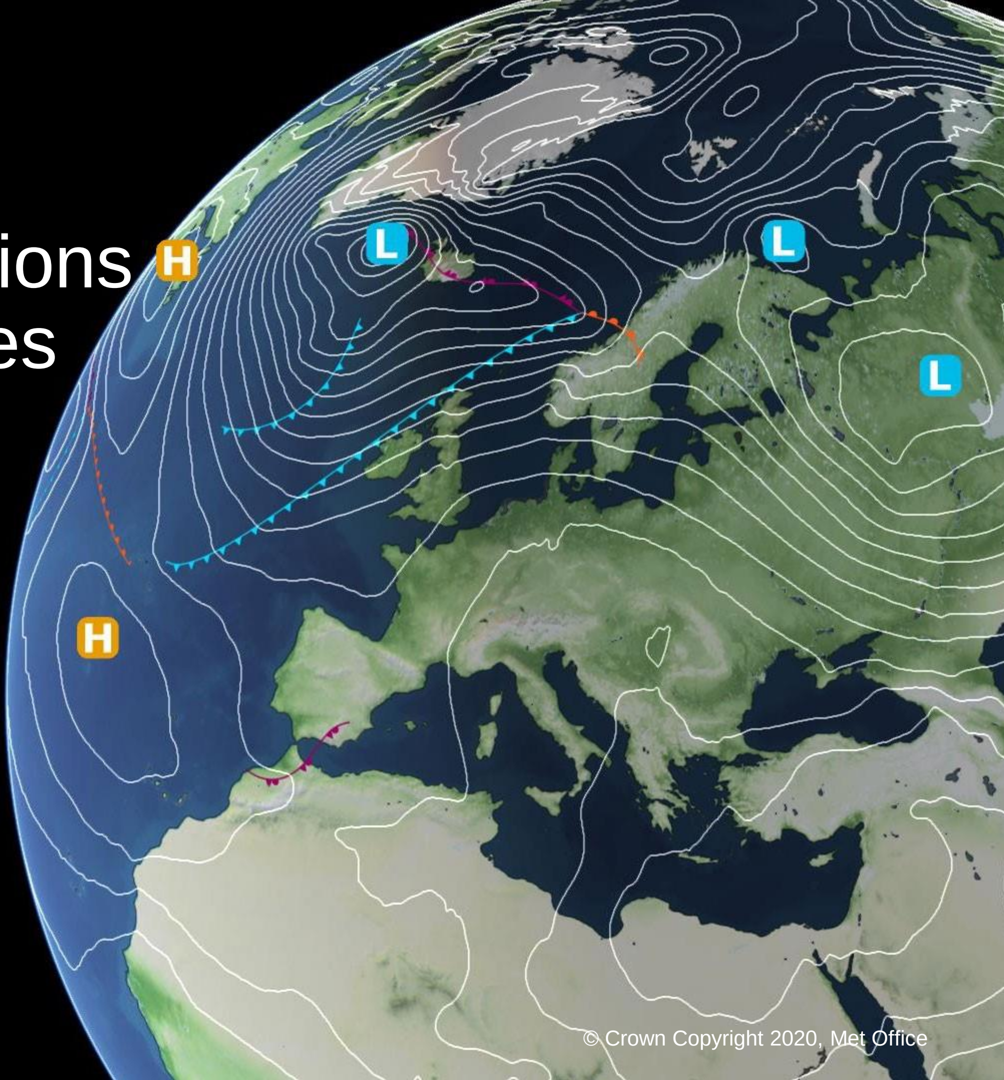
Machine Learning Applications in the Atmospheric Sciences



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Met Office Informatics Lab

RMetSoc Virtual Meeting, 5th March 2021

Talk Overview

- Brief intro to Machine Learning (ML) (to set the scene)
- Where is ML applicable to the Atmos. Sciences?
- Focus on themes and why they are important
- Challenges
- Conclusions

Brief intro to Machine Learning (ML)

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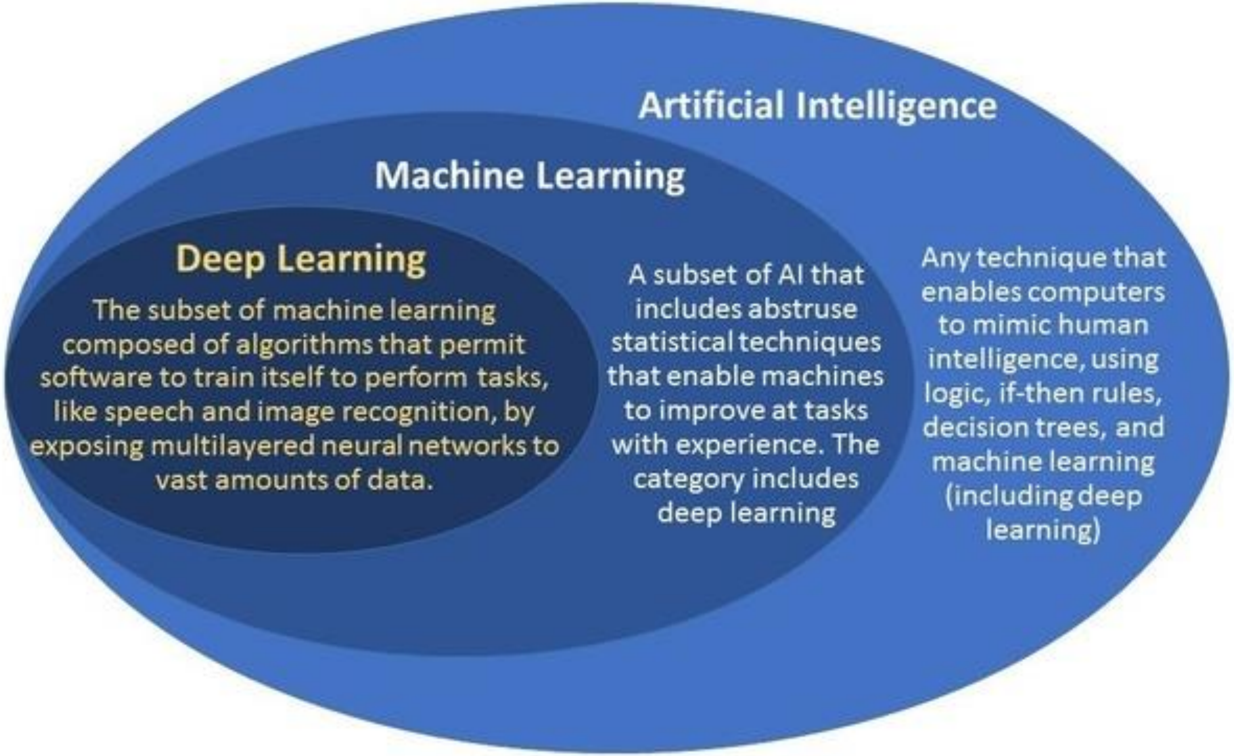
What is Machine Learning?

The definition has changed over time, but essentially ***comprises techniques that allow 'machines' to 'learn patterns autonomously from data'***

- Is considered a subdiscipline of AI and computer science
- Once a niche academic discipline but huge democratisation in last 5 – 10 years – availability of free online courses, open source software, data repos.
- Huge success of 'deep learning' (many-layered neural networks) in areas such as computer vision and natural language processing has stimulated take up in many domains

What is Machine Learning?



https://www.quora.com/How-are-AI-and-ML-different-and-what-could-be-a-possible-Venn-diagram-of-how-AI-and-machine-learning-overlap

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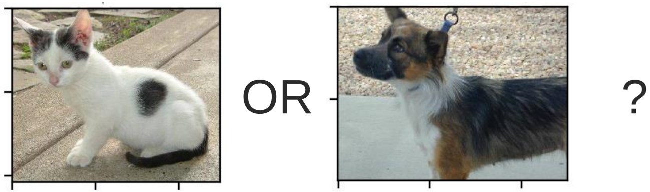
Types of Machine Learning

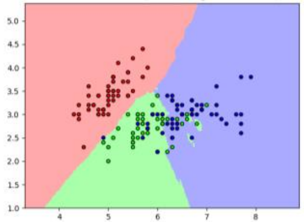


Broadly speaking, ML algorithms fall into three categories:

Supervised Learning

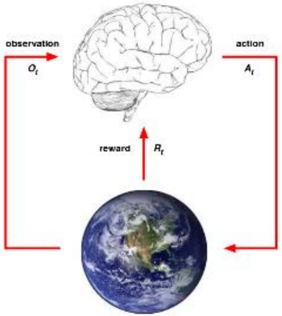
- Training phase where algorithm sees input and a correct output label
- Testing phase where only input is presented and label is predicted
- Example usage: predictive models (e.g. predict a house price given various features about the house), classification (is this picture of a cat or a dog?)

Unsupervised Learning



- Training data is unlabelled
- Training consists of ‘pattern finding’ to find similarities in data
- Example usage: clustering similar data points

Reinforcement Learning



- Data is in some sense presented ‘online’ via an environment
- The agent takes actions in the environment and learns how to reach a goal
- by how much reward (or not) it gets for its actions
- Example usage: Learning user preferences, optimising and tuning automated systems

What is Machine Learning?

- It's not new to atmospheric / environmental sciences! Have been using linear modelling, clustering even neural networks for many years
- It is the newer 'deep learning' techniques that are now of interest due to successes in other domains
- Weather and climate models are increasingly creating frequent, hi-res data. This is an opportunity for ML, which thrives on more data
- There are some challenges, however and I'll discuss these at the end

Machine Learning in the Atmospheric Sciences

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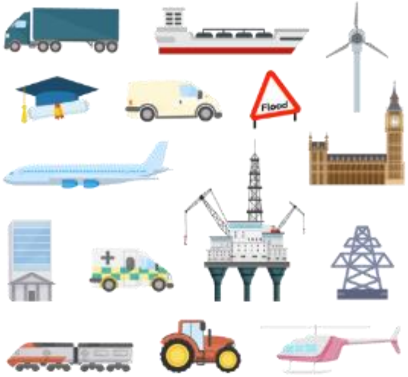
Observations → Simulation → Analysis → Products



Where does ML fit?.....potentially everywhere!

Application themes

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Simulation

Emulation of Parametrisations

Earth is complex with many processes interacting with each other on different scales. It is not always feasible to represent these accurately in conventional models

Subgrid scale physics is often represented by a parametrization rather than exact equations (e.g. clouds)

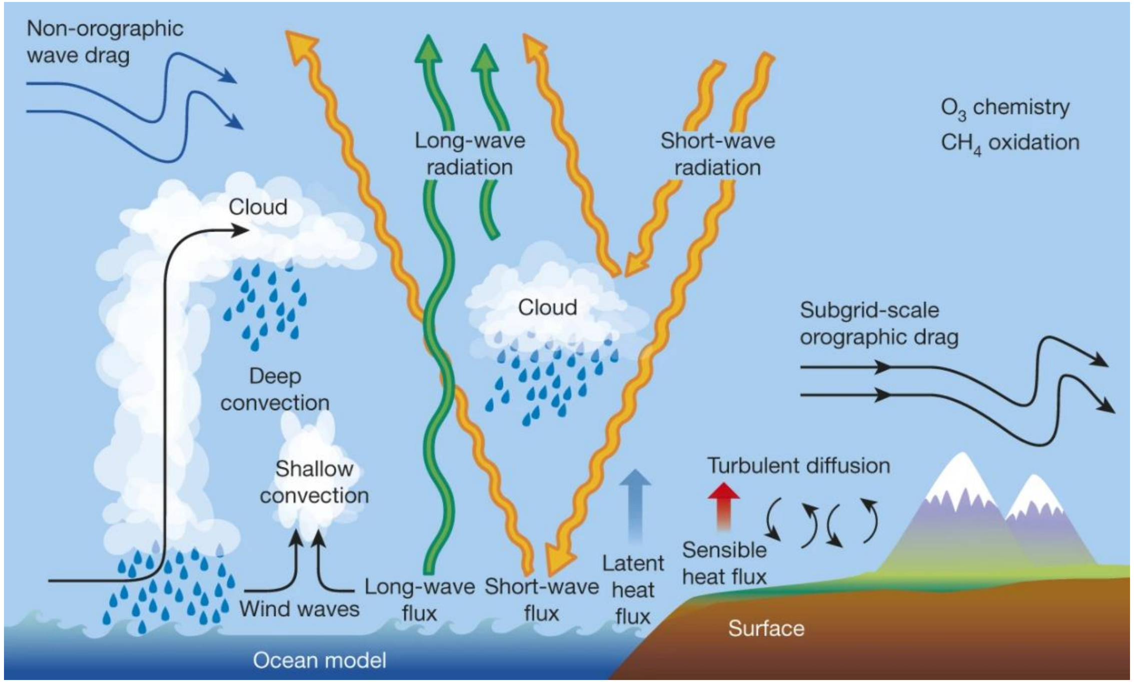

Figure from Bauer et al. (2015) 'The quiet revolution of numerical weather prediction'

Emulation of parametrisations

- An active area of ML research in many weather and climate organisations is to ‘emulate’ the parametrization with a ML model (usually a neural network)
- This involves ***supervised learning*** with input and output data – can often be higher resolution data than would be possible in the real model
- The goal is that the ML emulation is cheaper to run and may have better accuracy
- Has been done for atmospheric chemistry (Keller and Evans, 2019), gravity wave drag (Chantry et al. 2021), radiation (Krasnopolsky et al, 2010), convection (Rasp et al., 2018), cloud physics (Brenowitz and Bretherton, 2019)

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Simulation

Learning the model physics

- So a fair question might be…why do we need conventional models at all – can't ML learn the small-scale physics and large-scale dynamics in one go from observations data?
- Advantages - likely cheaper to run……we could make use of other hardware (e.g. GPUs)….we might learn new physics
- Disadvantages – why try and relearn physics that we already know…does the ML model really learn correct physics…is it as stable as a conventional model
- In early experiments the ML models were not fully stable, but this is improving
- Examples of this kind of work are: Dueben and Bauer, 2018; Scher and Messori, 2019; Weyn et al., 2019; Rasp and Theury, 2020

Learning the model physics

- There is some skepticism whether it is really feasible to learn an entire weather model.
- Hybrid solutions are looking very promising – here ML techniques are used but physical principles are built in to ensure good solutions.
- The ‘physics’ can be included in various ways: by augmenting with extra data, by constraining the learning to respect conservation, by building into the ML architecture.
- Examples of this kind of ‘physics-guided ML’ are: de Bézenac et al., 2017; Karpatne et al., 2018; Mohan et al., 2019; Beucler et al., 2021

Data analysis

- Huge amounts of data produced from weather and climate models, not to mention all the sources of observations data (at Met Office 18Tb a day….~ 9,000 HD films)
- Impossible for humans to look at it all
- Unsupervised ML can be used:
    - To assist processing and detection of interesting patterns in data
    - To aid understanding rather than replace conventional models

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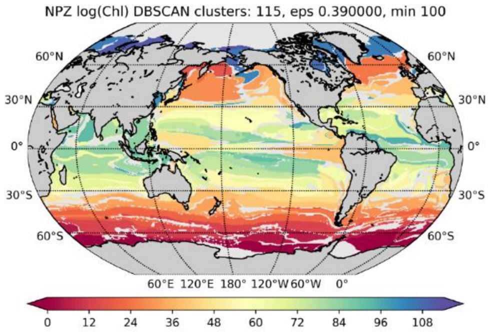
Analysis

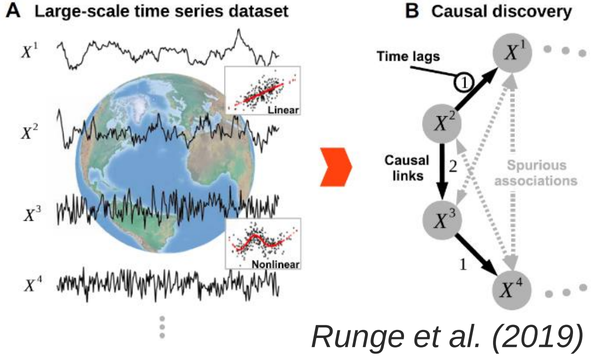
Data analysis

Interesting applications of this kind of work are

- Defining ocean biogeographical regions (Sonnewald et al., 2020)
- Using clustering techniques to understand climate model errors (Schuddeboom et al., 2019)
- Causal discovery / analysis for complex earth system processes – going beyond correlation (Runge et al, 2019; Nowack et al., 2020)



Sonnewald et al. (2020)



Runge et al. (2019)

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Products

Predicting extreme weather events

- Important to forecast extreme weather events accurately due to their potential impact on property and lives
- Tornados and Tropical Cyclones (TCs) are an example - predicting the initiation and evolution of them is an active research area
- A popular ML approach is to use Machine Vision techniques for object detection / segmentation / classification
- Like all supervised learning it requires a good ‘ground truth’ for training
- Work in this area has included detection of TCs in weather and climate model data (Matsuoka et al., 2018; Mudigonda et al., 2017), tracking the path of TCs (Mudigonda et al., 2017), Tornado prediction (Lagerquist et al., 2020)

Image sources: Wikipedia, cbbcnews

Predicting extreme weather events

- ML is already being used for for ‘nowcasting’ applications, especially rainfall. Observations data are used directly to provide very short term forecasts (e.g. < 1 hour ahead)
- This is generally much quicker than the time required to run a full forecast model
- Many examples of this kind of work apply methods first developed for video sequence prediction which use the newer deep learning neural network models suitable for spatio-temporal forecasting
- Given some input frames of radar or satellite data, the next few frames can be predicted
- Examples of work in this area are Shi et al. (2015), Lebedev et al. (2019) , Sønderby et al. (2020)

Image source: https://hmcoastguard.blogspot.com/2014/08/boscastle-floods-ten-years-on.html

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Products

Post-processing

- Post-processing of conventional weather/climate models is required for several reasons:
  - To create ‘products’ (forecasts, visualisations, tailor-made analyses for specific customers)
  - No model is perfect – post-processing also corrects known systematic errors
  - Downscaling - to produce hi-res site forecasts from lower-res model data

- ML for post-processing is being used in operational systems and is an active research area – for error correction, for uncertainty quantification…..

Post-processing

Examples of this kind of work:

- The US National Center for Atmospheric Research (NCAR) DiCast[1] system incorporates standard statistical and ML techniques for improved forecasts for many sectors (transport, agriculture, wind and solar energy
- UK Met Office incorporates ML to improve temperature forecasts at a particular site, e.g. Heathrow
- Ongoing research into ML for post-processing will feed into our new IMPROVER system.[2,3]
- Other research includes: improving snowfall forecasts (McCandless et al., 2011), improving rainfall forecasts (Taillardat et al., 2020), comparison of statistical and ML methods (Rasp and Lerch, 2018). Downscaling (Vaughn et al, 2020). For a review see Haupt et al. (2021)

1 https://ral.ucar.edu/solutions/products/dynamic-integrated-forecast-dicast%C2%AE-system
2 https://www.metoffice.gov.uk/research/weather/verification-impacts-and-post-processing
3 https://improver.readthedocs.io/en/latest/about.html

Wrapping up

Challenges

- Pull through to operational use. Some challenges in make research properly operational, also interfacing with existing systems.
- Labelled datasets (essential for supervised learning, and a lot possibly needed in complex atmos. domain). The success of deep learning has partially arisen from the availability of benchmark datasets
- Understanding what your ML system did and what it means. Scientists are rightly concerned about the 'black box' approach to ML. ML (apart from well-established linear methods) has not had the same degree of rigour applied as to statistical modelling.
- The ‘ethics’ angle – has lagged behind the technology dev in ML field but is a hot topic. Anything that influences decision making and peoples’ livelihoods must be considered
- Requires a combo of skills unlikely to be present in any one role (the ‘unicorn’): Domain science expertise, Data engineering, Software engineering, ML expertise

Conclusions

- A massive uptake in Atmos. Sci since I started working in this area (last 5 years).
- More publications in Atmos sci journals, also ML sessions in main conferences in our domain
- Tip of the iceberg in potential applications. The ML field is expanding rapidly with new techniques and so far we are not exploiting much of this new research.
- ML should be part of the scientist's toolset, it's just advanced stats :-)
- Outlook: where will we be in 10 years?

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Outlook: Where will we be in 10 years?

The uncertainty range is still very large...

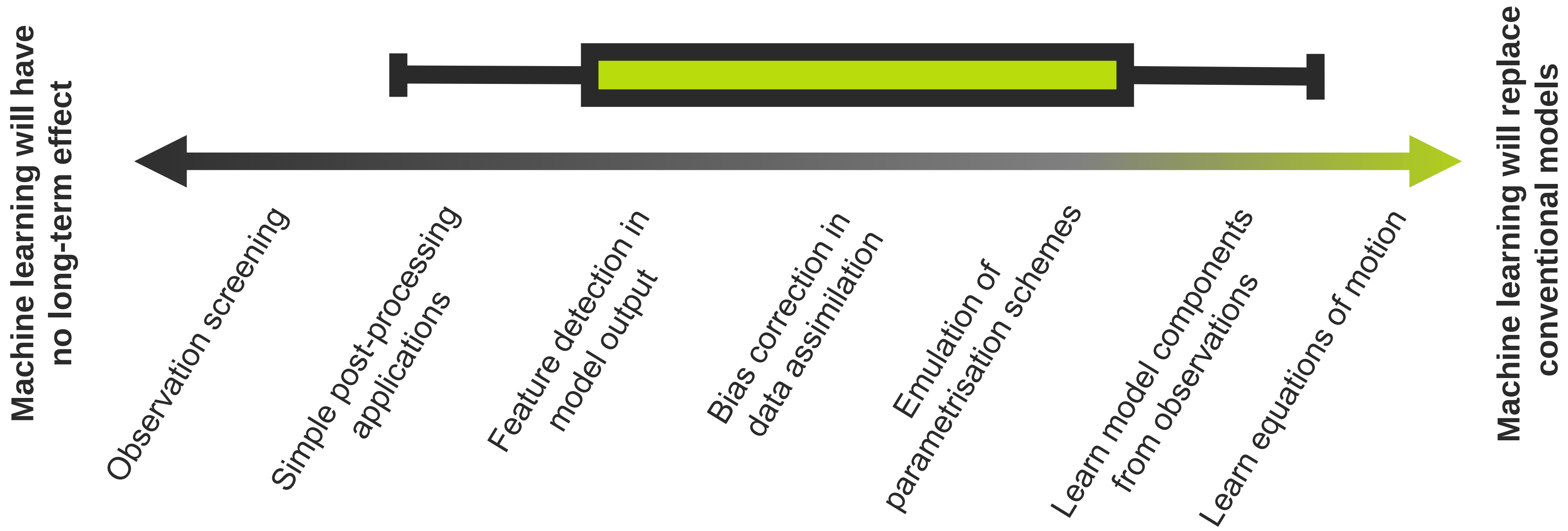

Figure courtesy Peter Dueben, ECMWF

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Thank You!
Questions?