# NWP in 2030?

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https://arxiv.org/abs/2007.04830

# Why Bother?

Kerala 2018 (Partha Mukhopadhyay)

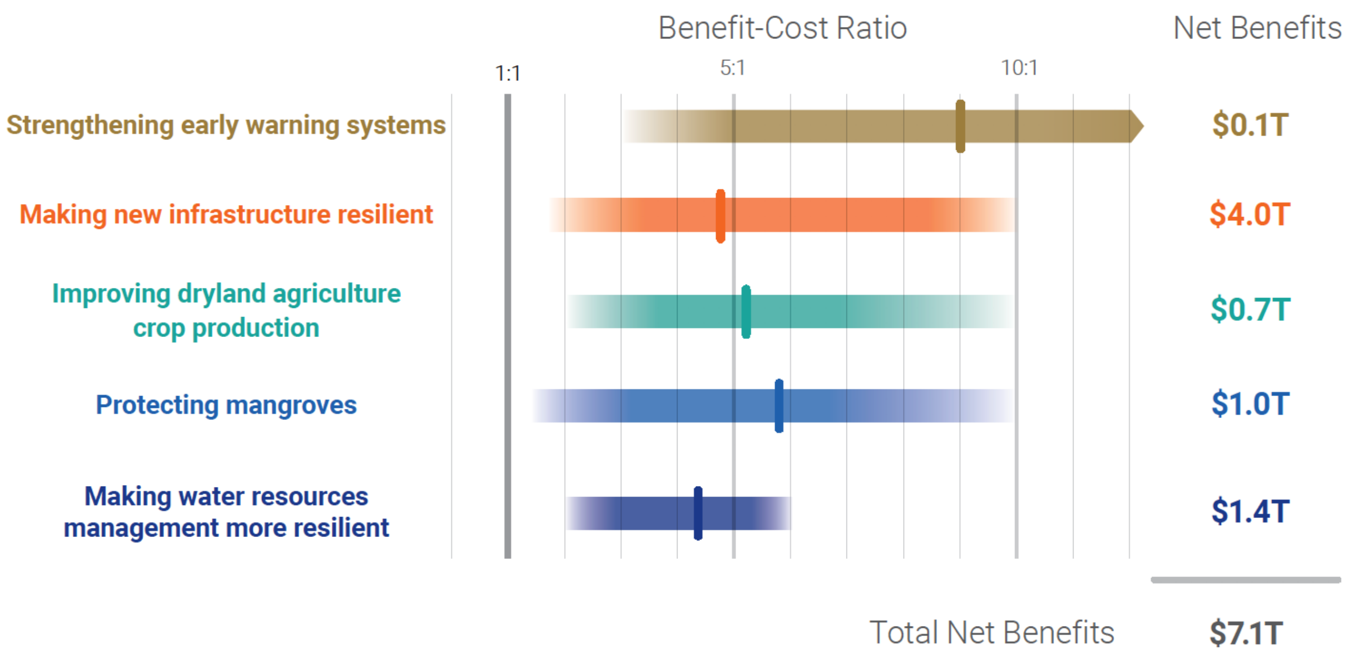
NWP can play a vital role in helping society become more resilient to the increasing extremes of climate.

GLOBAL COMMISSION ON ADAPTATION

#AdaptOurWorld

# ADAPT NOW: A GLOBAL CALL FOR LEADERSHIP ON CLIMATE RESILIENCE

**FIGURE ES.1** Benefits and Costs of Illustrative Investments in Adaptation




*Note*: This graph is meant to illustrate the broad economic case for investment in a range of adaptation approaches. The net benefits illustrate the approximate global net benefits to be gained by 2030 from an illustrative investment of $1.8 trillion in five areas (the total does not equal the sum of the rows due to rounding). Actual returns depend on many factors, such as economic growth and demand, policy context, institutional capacities, and condition of assets. Also, these investments neither address all that may be needed within sectors (for example, adaptation in the agricultural sector will consist of much more than dryland crop production) nor include all sectors (as health, education, and industry sectors are not included). Due to data and methodological limitations, this graph does not imply full comparability of investments across sectors or countries.
*Source*: World Resources Institute.

Craig Bishop's question to Andy Brown.

https://doi.org/10.1038/d41586-020-01484-5

# News & views

Climate change

## Short-term tests for long-term estimates

Tim Palmer

Six-hour weather forecasts have been used to validate estimates of climate change hundreds of years from now. Such tests have great potential – but only if our weather-forecasting and climate-prediction systems are unified.

How sensitive is climate to atmospheric carbon dioxide levels? For a doubling of $CO_2$ concentration from pre-industrial levels, some models predict an alarming long-term warming of more than 5 °C. But are these estimates believable? Writing in the *Journal of Advances in Modeling Earth Systems*, Williams *et al.*[1] have tested some of the revisions that have been made to one such model by assessing its accuracy for very short-term weather forecasts. The results are not reassuring – they support the estimates.

There is little doubt, at least among those who understand the science, that climate change is one of the greatest challenges facing humans in the coming decades. However, the extent to which unchecked climate change would prove catastrophic rests on processes that are poorly understood. Perhaps the most important of these concern the way in which Earth's hydrological cycle – which includes the evaporation, condensation and movement of water – will react to our warming planet.

One of the key problems is how clouds adjust to warming[2]. If low-level cloud cover increases, and high-level cloud decreases, then clouds will offset the warming effect of increased atmospheric $CO_2$ concentrations and thereby act as a negative feedback, or damper, on climate change, buying us some breathing space. By contrast, if there is positive cloud feedback – that is, if low-level clouds decrease with warming and high-level clouds increase – then, short of rapid and complete cessation of fossil-fuel use, we might be heading for disaster.

So what have clouds been doing as global warming has slowly taken hold? Trends in global cloud cover can be estimated only from space-based observations (Fig. 1). However, cloud data sets derived from multiple satellites over several decades suffer from spurious artefacts related to changes in satellite orbit, instrument calibration and other factors[3]. These artefacts are particularly large when estimating globally averaged cloud cover, currently preventing any reliable estimation of trends in one direction or the other.

In lieu of observational evidence, we must turn to computational models of the climate system. But there is a problem. Clouds are on too small a scale to be represented using the laws of physics in current climate models. Instead, they are represented by relatively crude, computationally cheap bulk formulae known as parameterizations. These do encode some basic ideas of cloud physics – clouds' dependence on the ambient temperature, humidity and vertical air velocity, for example – but they are far from being *ab initio* estimates. Hence, the role of clouds in climate change is crucial but uncertain[4].

The cloud-feedback problem has been brought sharply into focus in recent months as results have been emerging from the dozens of climate-change models in an ensemble called the Coupled Model Intercomparison Project (CMIP6; see go.nature.com/3garyzc). Projections of future climate from this global effort have fed into the Sixth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC), due next year.

Some of the latest-generation models in CMIP6 now indicate climate sensitivities exceeding 5 °C (refs 5–7). Here, climate sensitivity refers to the global warming after climate has equilibrated to a doubling of $CO_2$ concentration relative to pre-industrial levels, an equilibrium that might take a few hundred years to establish[8]. These sensitivity values are outside the range of those produced by the CMIP5 ensemble, which fed into the previous IPCC Assessment Report[8] in 2013. They seem to have arisen largely because of revisions to how cloud microphysics is represented,

ESA/NASA

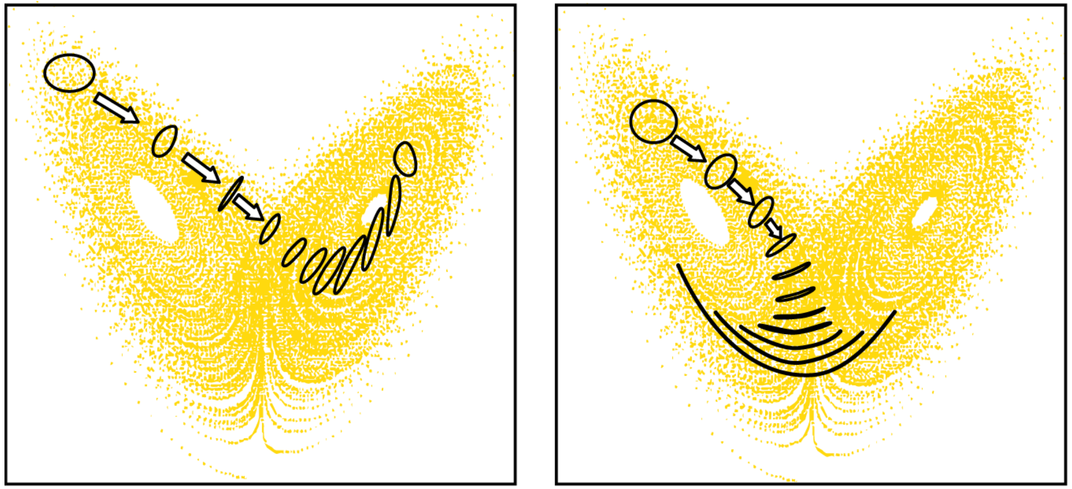
**Figure 1 | Cloudy skies, viewed from space.** How clouds will adjust to a warming climate is difficult to predict, but Williams *et al.*[1] have used short-term weather forecasts to assess whether recent revisions to long-term climate models are getting us nearer to the truth.

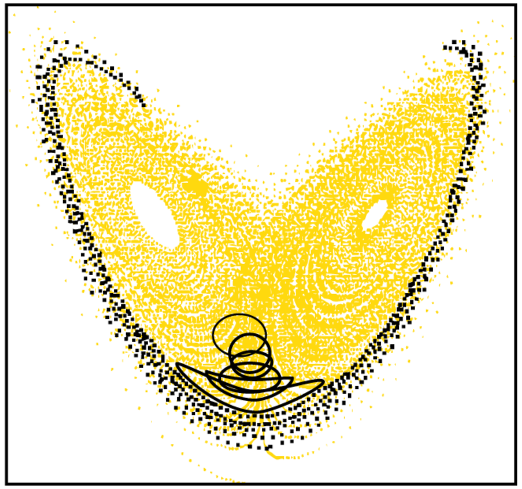
# To improve NWP, do we need more observations or better models?

- A key problem in the medium-range is an inability to assimilate the key information in observations into the forecast model. (Rodwell, 2013). This is often a model resolution problem.
- Forecast skill of precip in tropics (where circulations are convectively forced) is systematically worse than in extratropics.
- John Le Marshall's question to Andy Brown.
- In the late medium-range, models generate systematic errors due to systematic deficiencies in the heuristic formulae (aka parametrisations) used to represent unresolved processes.

# High-resolution (1-3km) global ensembles

- Better representation of extremes
- Better able to assimilate observations
- No need for some key parametrisations – smaller systematic errors





Deterministic prediction within ”the limit of deterministic predictability” makes no scientific sense at all!

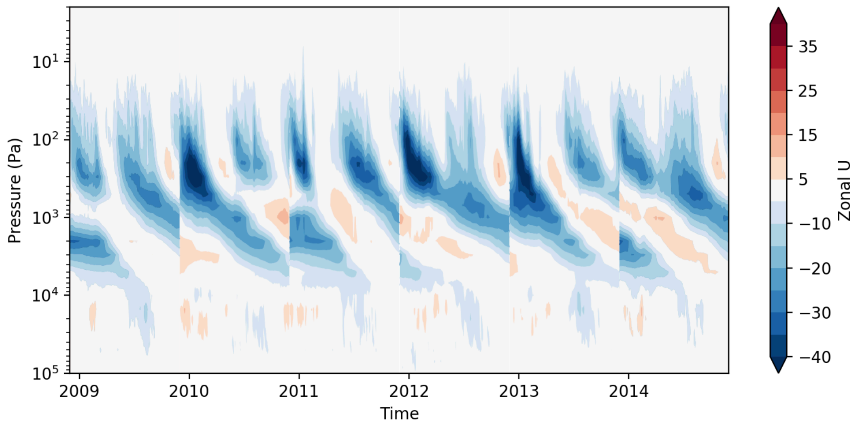
# High-resolution (1-3km) global ensembles – a computational challenge even by 2030.

- Use of AI for parametrisations (in nonlinear model and in tangent linear model)
- Use of reduced-precision (single and maybe even half-precision) modelling
- Domain-specific languages.

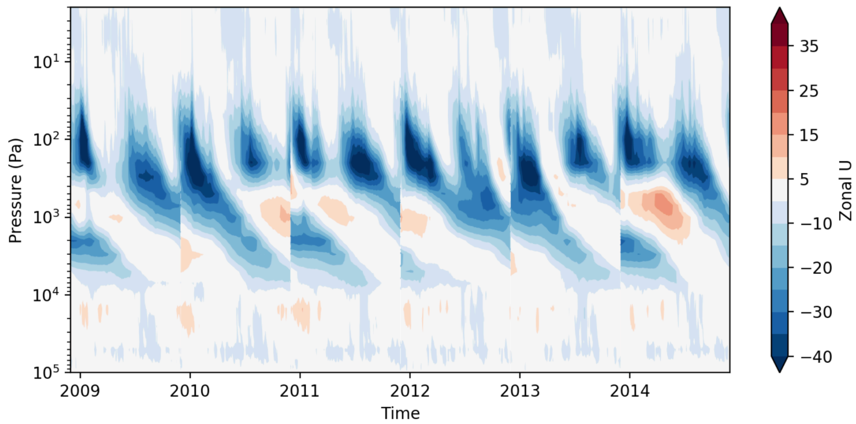
# Neural networks for efficient Gravity Wave Drag parameterization

- Emulate existing Non-Orographic Gravity Wave Drag (NOGWD) scheme from ECMWF's IFS model.
- Use fully connected neural network trained on 1-year of data.
- Inputs: pressure, velocity & temperature profiles
  Outputs: velocity tendency profiles.
- Neural network performs well when coupled back into IFS, offline speed testing finds NN scheme is 2x faster.

Existing NOGWD scheme




Neural network NOGWD scheme




Year long simulations of IFS using existing or NN gravity wave drag schemes. Forced with observed SST. Plotting equatorial zonal jet to show the descent of the Quasi-Biennial Oscillation. The previous GWD scheme (not plotted) failed to produce this descent.

Mat Chantry

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Research

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http://dx.doi.org/10.1098/rsta.2013.0391

One contribution of 14 to a Theme Issue 'Stochastic modelling and energy-efficient computing for weather and climate prediction'.

**Subject Areas:**
atmospheric science, oceanography, computational physics

# More reliable forecasts with less precise computations: a fast-track route to cloud-resolved weather and climate simulators?

T. N. Palmer

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Oxford Martin Programme on Modelling and Predicting Climate

This paper sets out a new methodological approach to solving the equations for simulating and predicting weather and climate. In this approach, the conventionally hard boundary between the dynamical core and the sub-grid parametrizations is blurred. This approach is motivated by the relatively shallow power-law spectrum for atmospheric energy on scales of hundreds of kilometres and less. It is first argued that, because of this, the closure schemes for weather and climate simulators should be based on stochastic–dynamic systems rather than deterministic formulae. Second, as high-wavenumber elements of the dynamical core will necessarily inherit this stochasticity during time integration, it is argued that the dynamical core will be significantly over-engineered if all computations, regardless of scale,

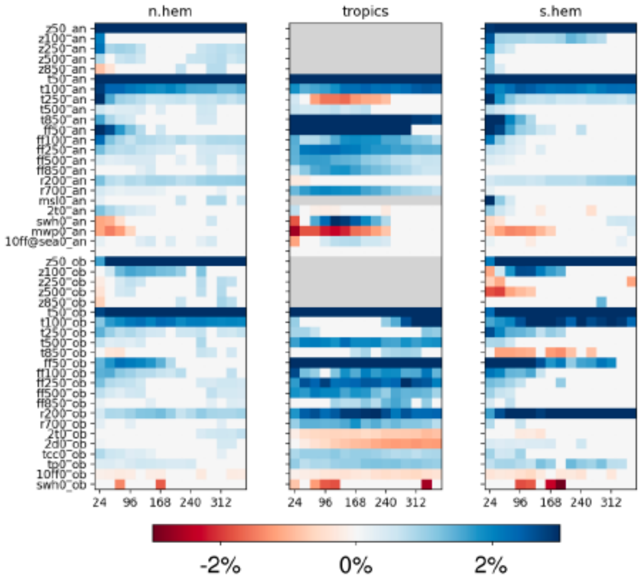
If the parametrization problem is inherently stochastic, why are we running our model with 64-bit precision? Makes no sense!

With thanks to Mat Chantry, Peter Dueben, Sam Hatfield, Adam Paxton, Leo Saffin.

# More accuracy with less precision

## Single-precision in the atmosphere (status)

- Single-precision atmosphere **operational default** for HRES and ENS (not DA) from Cy47r2 onwards (∼ January 2021)
- **1.7× times speed-up** compared with double-precision
- Allows free upgrade from 91 to 137 levels → improvement in forecast skill



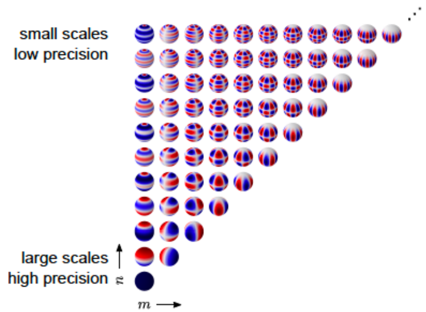

CRPS improvement
(TCo639L137SP vs. TCo639L91DP)

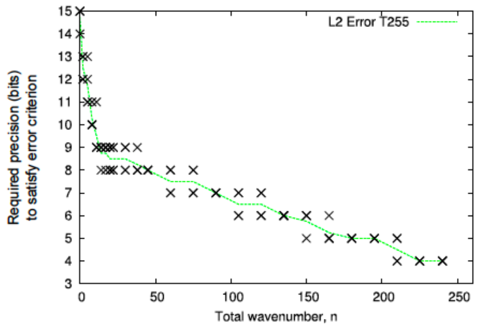


Simon Lang and colleagues at ECMWF

# Scale-selective precision (1)

High-precision for large scales, low-precision for small scales?

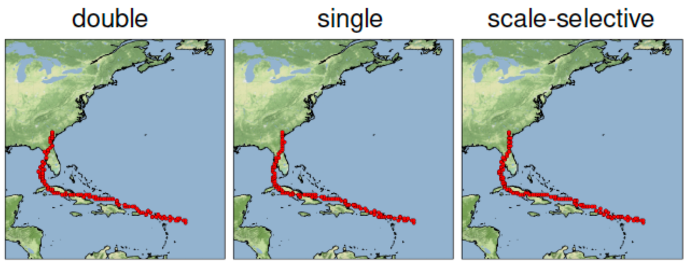



[Chantry et al., 2018]



# Scale-selective precision (2)




Hurricane Irma core position

Average precision of “scale-selective” (across all wavenumbers): **8.6 significand bits**

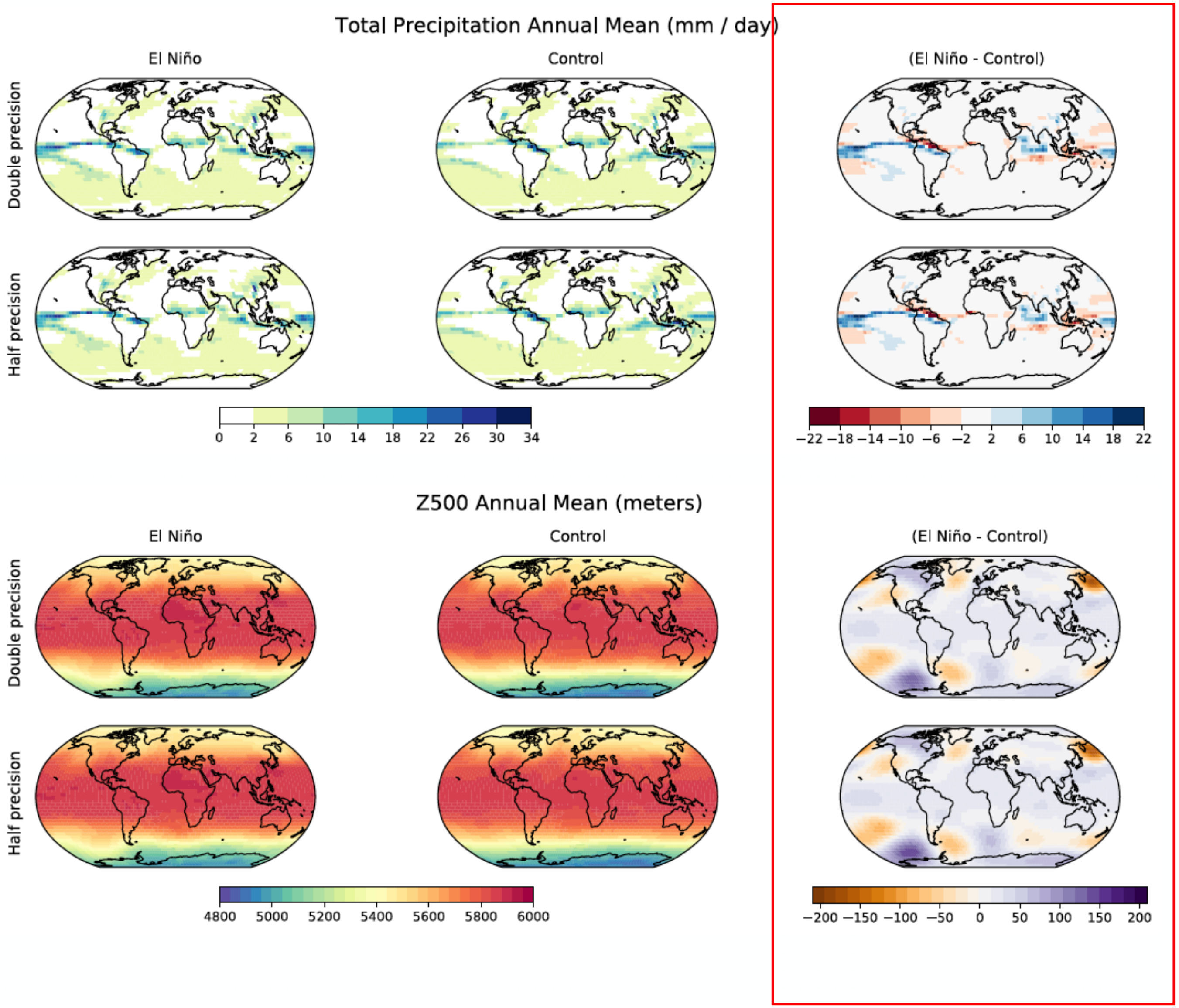


# Towards Half Precision

Mat Chantry, Peter Dueben, Sam Hatfield

# Half-precision on climate timescales.

- An analysis of reduced precision SPEEDY.
- A coarse resolution (3.75° × 3.75°) atmosphere only, primitive equation model (prescribed SSTs) with simplified parameterisations.
- The 16-bit (deterministic) version of the code has held up to first tests.

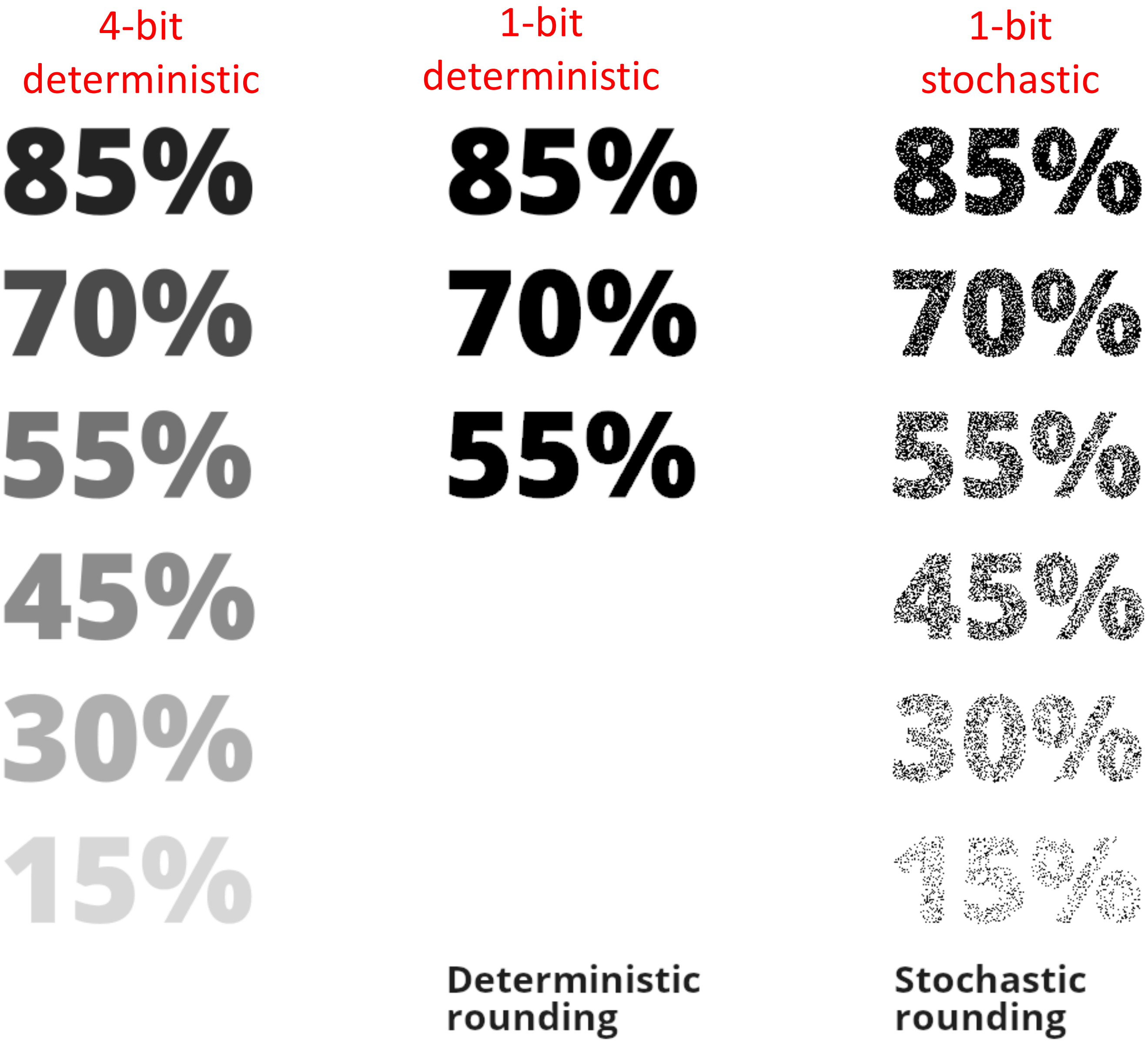



Adam Paxton, Leo Saffin, Mat Chantry

1. **Fugaku** Supercomputer at 16 bit ≈ Exascale.

   *(and nothing is lost from running at low precision)*


ARM chips support mixed precision in Fortran

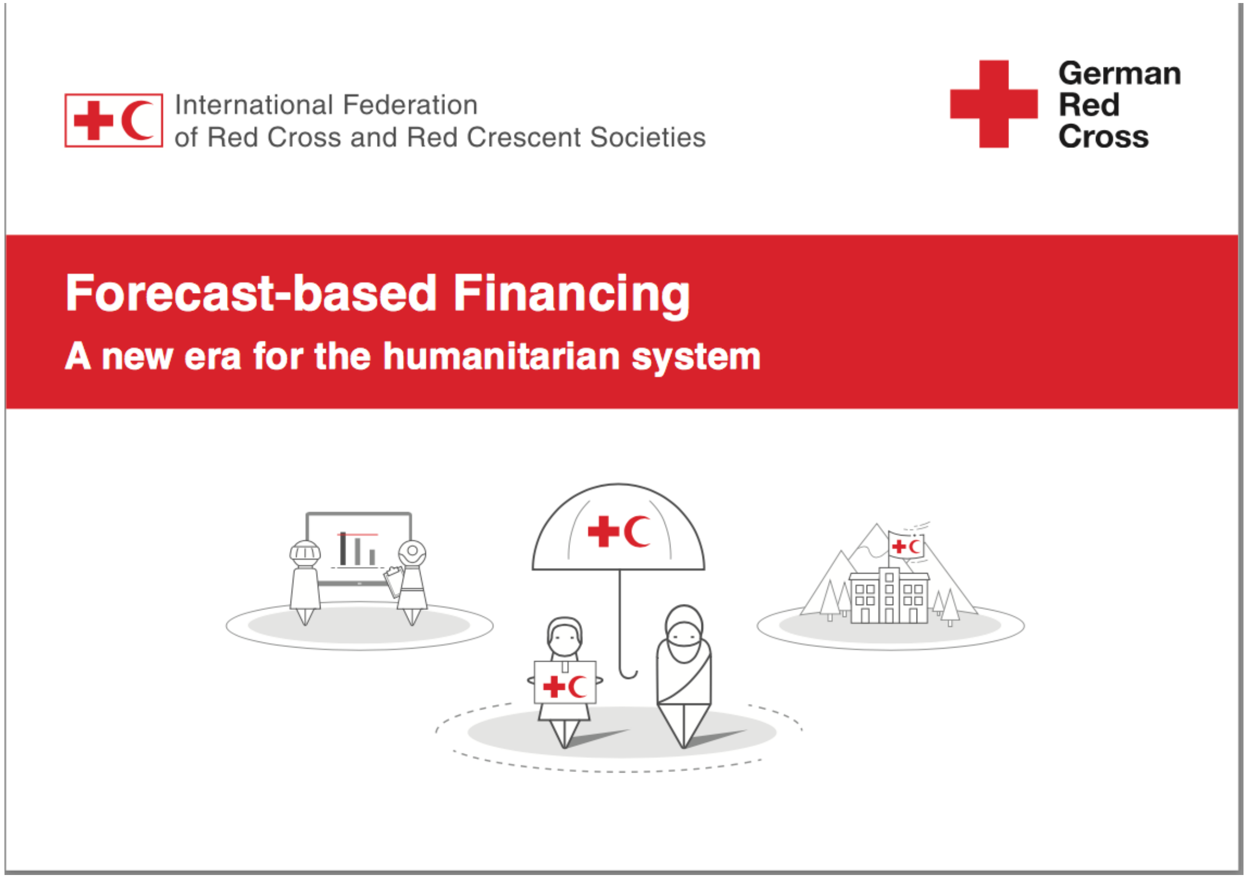



Noise can be a positive resource!

# Downscaling and Calibration

- Necessary even with a 1km model

- How to do this:
  - LAMs
  - AI


International Federation
of Red Cross and Red Crescent Societies

German
Red
Cross

Forecast-based Financing

A new era for the humanitarian system

Needs fully reliable probabilistic triggers for regionally specific extreme events in the medium range.

# Advantage of LAMs

- Based on the laws of physics.
- Terrific results from Charmaine Franklin (yesterday)

# Disadvantages of LAMs

- We will need to run them over full medium range if they are to usefully guide e.g. F-b-F.
- Need ensembles (e.g. for probabilistic triggers).
- Need significant reforecasts in order that forecast data can be calibrated and fed into impact/application models.
- Few if any NMSs have the resources to do this adequately: none in the developing world where extreme weather is most severe.

# Advantages of AI

- National-specific AI schemes can be developed at NMSs using national observational datasets for training.
- A key role for maintaining both data and human resources at the national level.
- Easily run over long forecast ranges.

# Disadvantages of AI

- This is an untested area.
- Do we have adequate training data?
- Can they cope with record-breaking extremes, not seen in the training data?

Example of AI downscaling scheme



# Stochastic Super-Resolution for Downscaling Time-Evolving Atmospheric Fields with a Generative Adversarial Network

Jussi Leinonen, Daniele Nerini and Alexis Berne



***Abstract*—Generative adversarial networks (GANs) have been recently adopted for super-resolution, an application closely related to what is referred to as "downscaling" in the atmospheric sciences. The ability of conditional GANs to generate an ensemble of solutions for a given input lends itself naturally to stochastic downscaling, but the stochastic nature of GANs is not usually considered in super-resolution applications. Here, we introduce a recurrent, stochastic super-resolution GAN that can generate**

Like many other image processing applications, super-resolution has benefited from the introduction of the techniques of deep learning and particularly convolutional neural networks (CNNs). Early attempts at super-resolution using deep CNNs focused on finding image quality metrics that could serve as loss functions that produce sharp images [5]–[7]. More recently, generative adversarial networks (GANs)



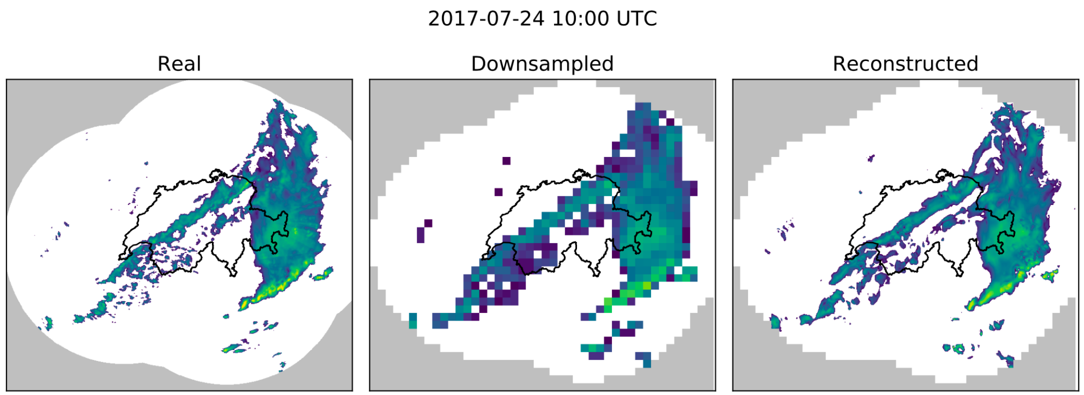



Fig. 7. An example of the results of the GAN applied to full frames of the June–August 2017 data from the MCH-RZC dataset, showing the situation of July 24 at 10:00 UTC. The gray areas mask the points unavailable due to lack of radar coverage. The borders of Switzerland are shown in the middle in order to provide spatial context. Left: the original frame. Middle: the downsampled version fed to the generator. Right: The high-resolution frame reconstructed by the GAN.

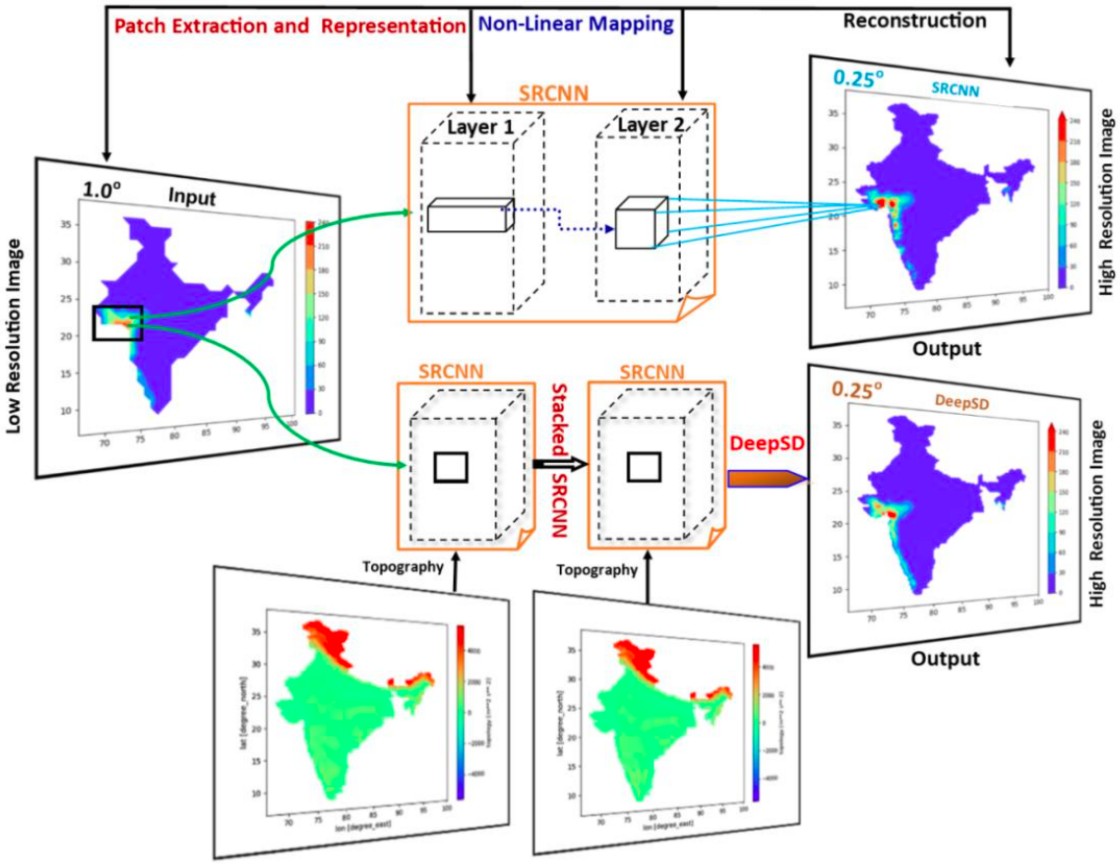
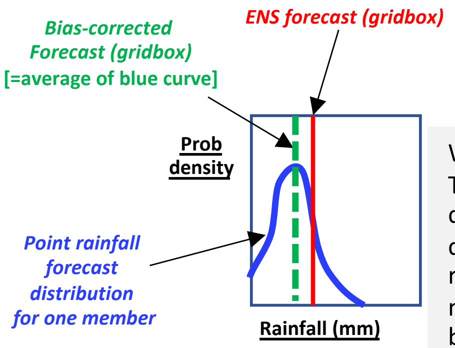



**Fig 2**: An overview of SRCNN and DeepSD methods. In the DeepSD, the downscaling is done in steps rather than a direct 4x or 8x resolution. Also, DeepSD used multivariable inputs.

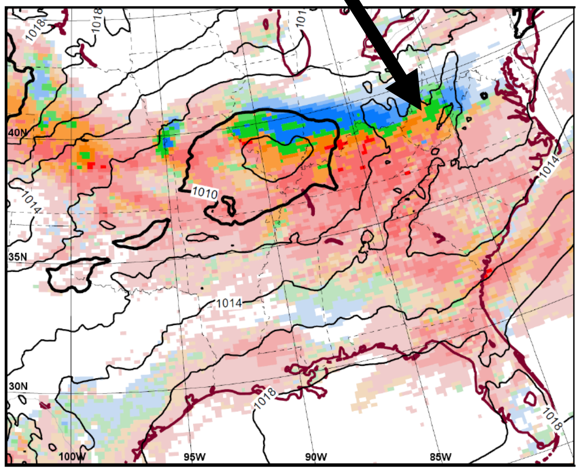
# ecPoint post-processing

c/o Tim Hewson, ECMWF



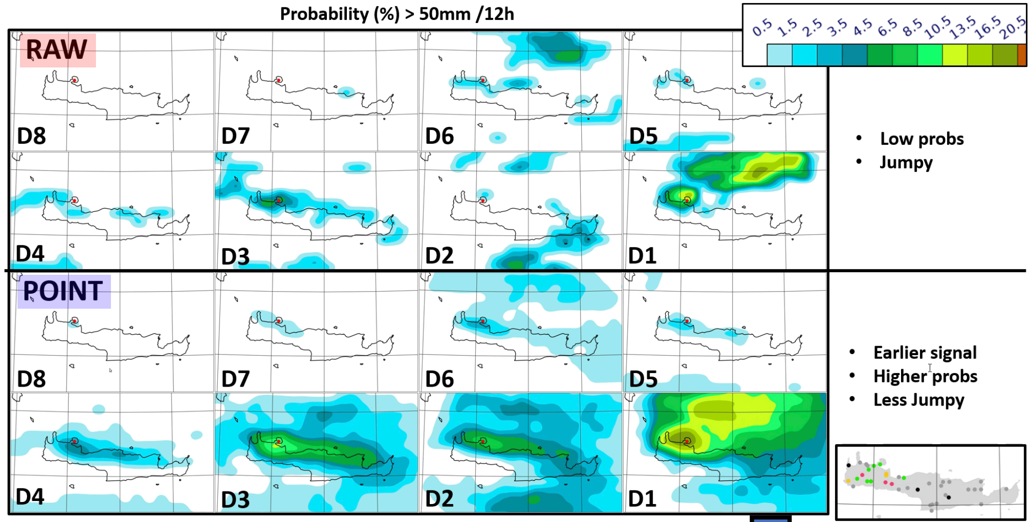

Which Weather Type is diagnosed determines how red line is mapped onto blue line

One ENS member
One gridbox



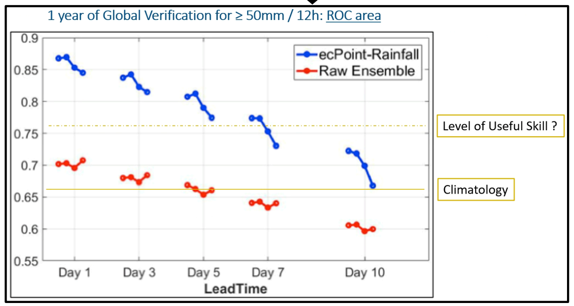

Gridbox Weather Types (**one member**, one time) + mslp

Forecast for gridbox for given lead time is derived by merging together (averaging) blue curves from all ensemble members




Forecast example for flash floods in western Crete

- Calibration is non-local, it needs just 1 year of 48h Control forecasts
- Convective and large-scale rain are post-processed very differently
- All ecPoint forecasts can be easily decomposed and understood (gives physical insights)




Convection-resolving ensembles:

"In two 1-year verification comparisons, with limited area ensembles, with and without modern post-processing methods applied, for two relatively mountainous European regions, ecPoint performed as well or better"

ECMWF

# Data Assimilation

- Blending reduced precision and AI
  - Tangent linear / adjoint of of Neural Net based parametrization is simple
  - Allows precise adjoint modelling with full physics at low precision
  - Can we assimilate observations into a model which includes stochastic AI-downscaled software?

# NWP for 2030

- Need to improve early warning systems on timescale of a week or more so that precautionary actions can be taken. Part of improving climate resilience.
- Global ensembles vital, but we must develop convective-permitting models.
- We have to develop much more efficient algorithms to enable better use to be made of exascale computing – AI and stochastically rounded low precision, enormous potential to improve data assimilation schemes.
- Downscaling and calibration are going to be vital tools. AI holds more promise than LAMs.
- Forecasters role much more in interacting with users to find the most appropriate probabilistic products.