Forecasting Global Point-Rainfall

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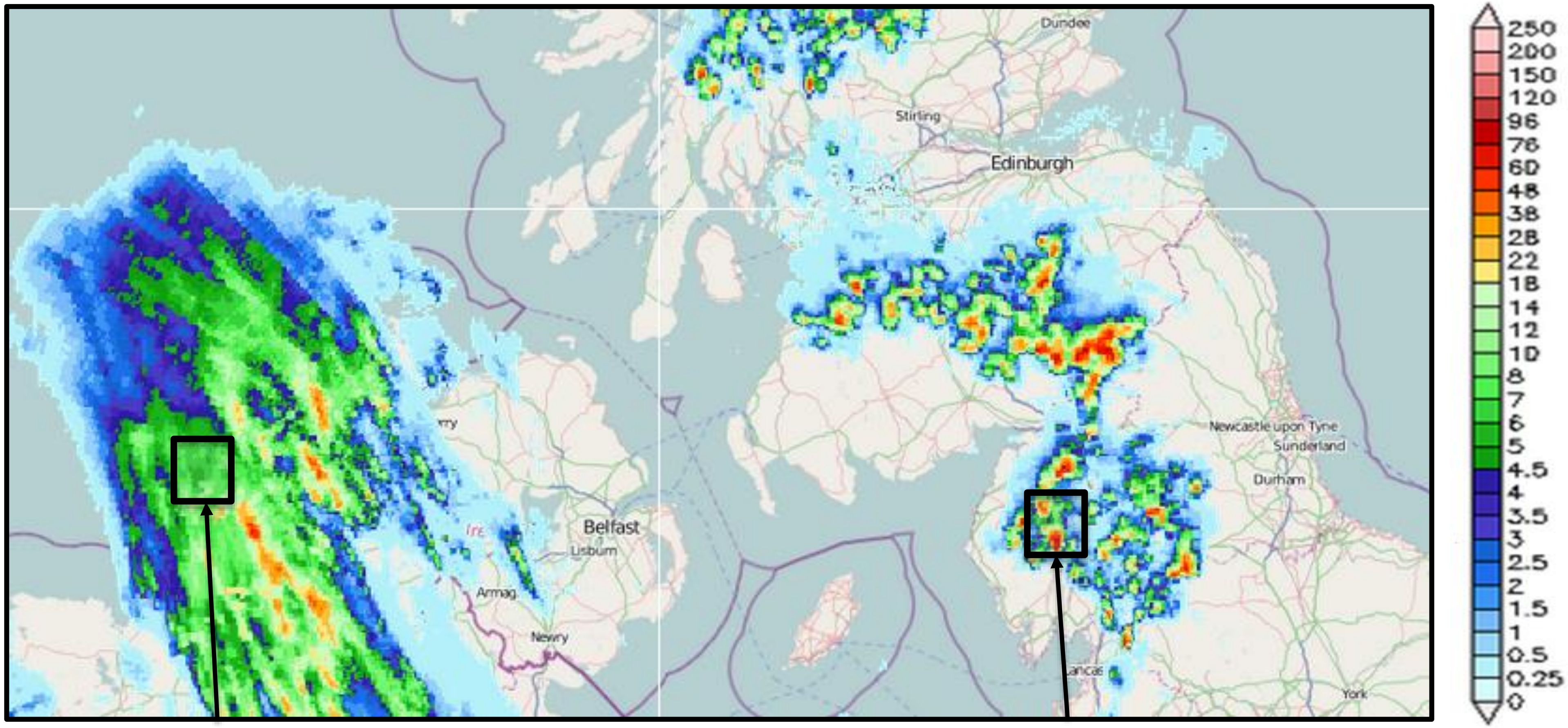
The Concept

Mostly we want to forecast extreme point-rainfall

Anticipate different degrees of sub-grid variability (and account for model biases)

12h radar-derived totals (in mm)



5-12mm (point values)
Mean ~ 8mm (model grid-box forecast)

0-80mm (point values)
Mean ~ 6mm (model grid-box forecast)

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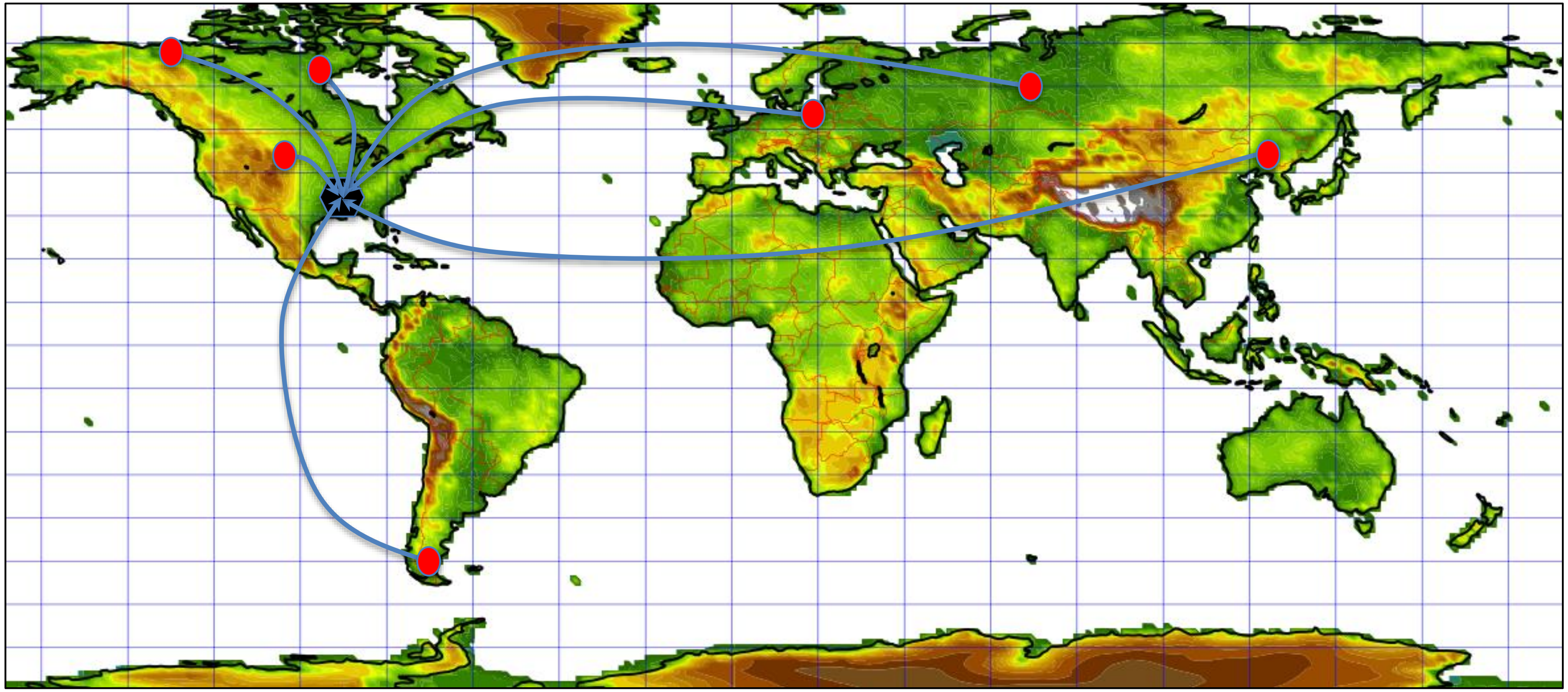
The (Innovative) Approach

We want to forecast rainfall for, let's say Louisiana, and the conditions are: mainly convection, light winds, in summer. Then, we can pose the following question: **how the model performed, <u>at a short range</u>, in other sites with similar conditions (relatively flat areas, similar forecast conditions)?**



Errors at those sites, at those times, provide a good guide to assess the model reliability for those particular conditions and indeed, **provide a pdf to post-process the ensemble member that predicted the same conditions**.

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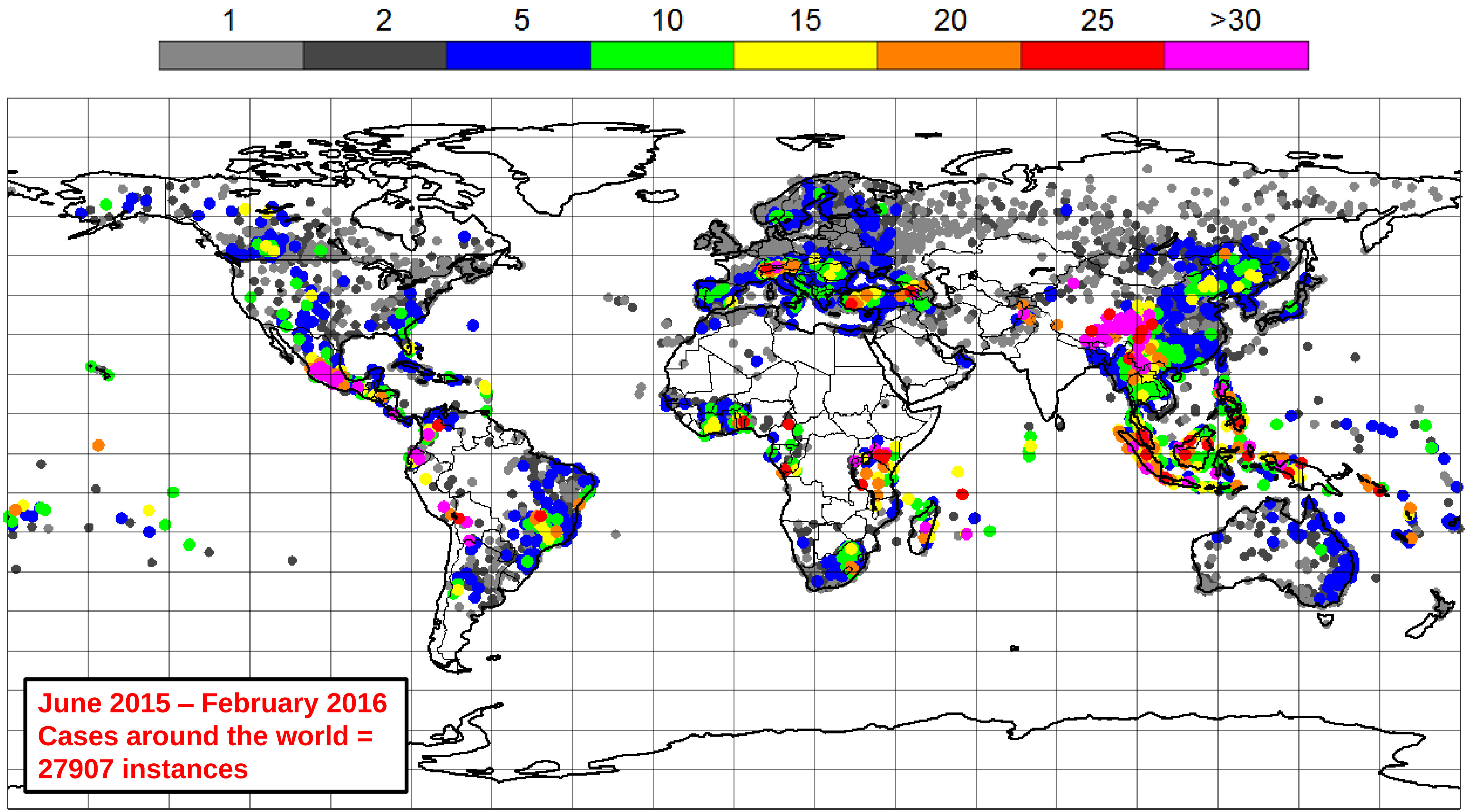
Extreme Weather in UK (mainly convective precipitation, light winds, medium values of total precipitation)



The (Innovative) Approach

- Use of remote sites immediately provides a massive training dataset, from a short training period (if we use global data)
- For calibration we focus on short range forecasts, to minimize random errors
- The *actual forecast itself* can be for <u>any lead time</u>, <u>for any gridbox</u>
- In this way we create probabilistic forecasts for points, using global conditional verification as a means of calibrating the raw gridbox forecast

The Approach with an Ensemble

- Here one adds together (and normalizes) the pdfs created as above for each ensemble member
- Each ensemble member may of course not predict the same meteorological conditions and those would be post-processed in the same general way, but using training data for other contions (and values of other variables as relevant, and as represented in those members)

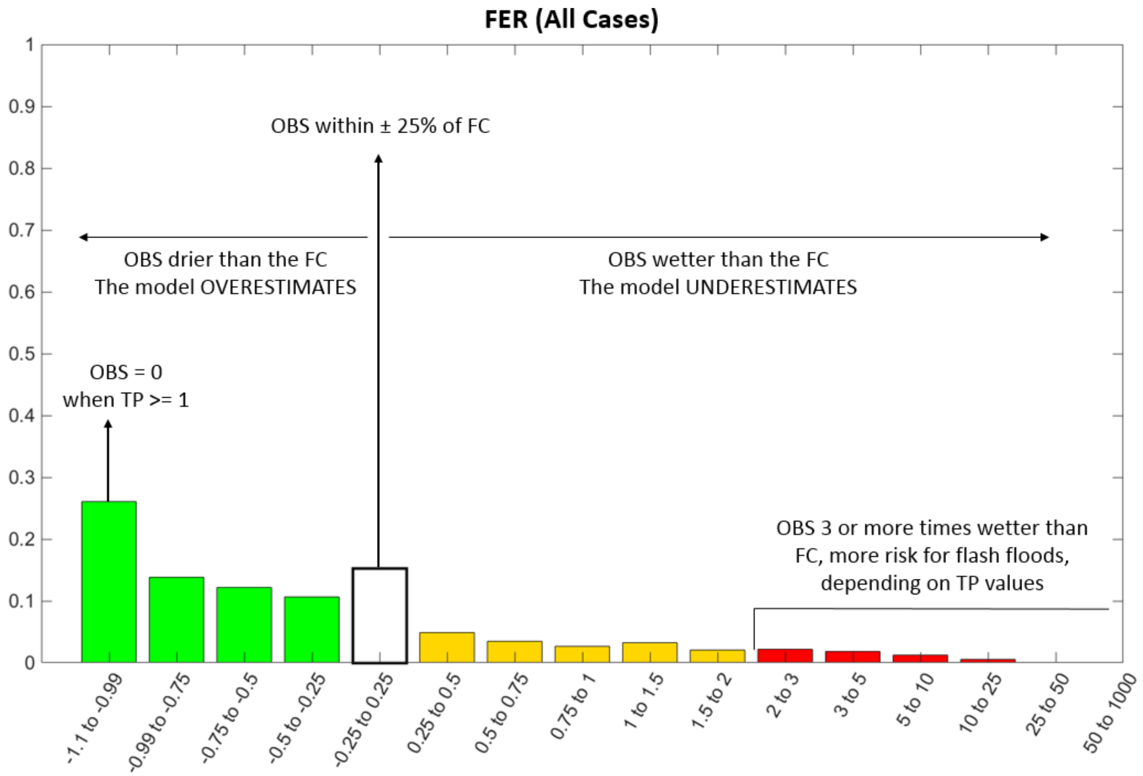
Compare O_{point} with $F_{gridCAL}$ (where tp>=1) over all available cases

to determine →

Forecast Error Ratio

$$FER = \frac{O_{point} - F_{gridCAL}}{F_{gridCAL}}$$

A probability density function (pdf) for all FER, *Ω(FER), can be generated*.
It is called ***Mapping Function.***



The efficacy/utility of this procedure
Creation of Multiple Mapping Functions for n physically & significantly different Weather Types (WTs)
to capture **sub-grid variability within the model grid-box** and **model biases**.

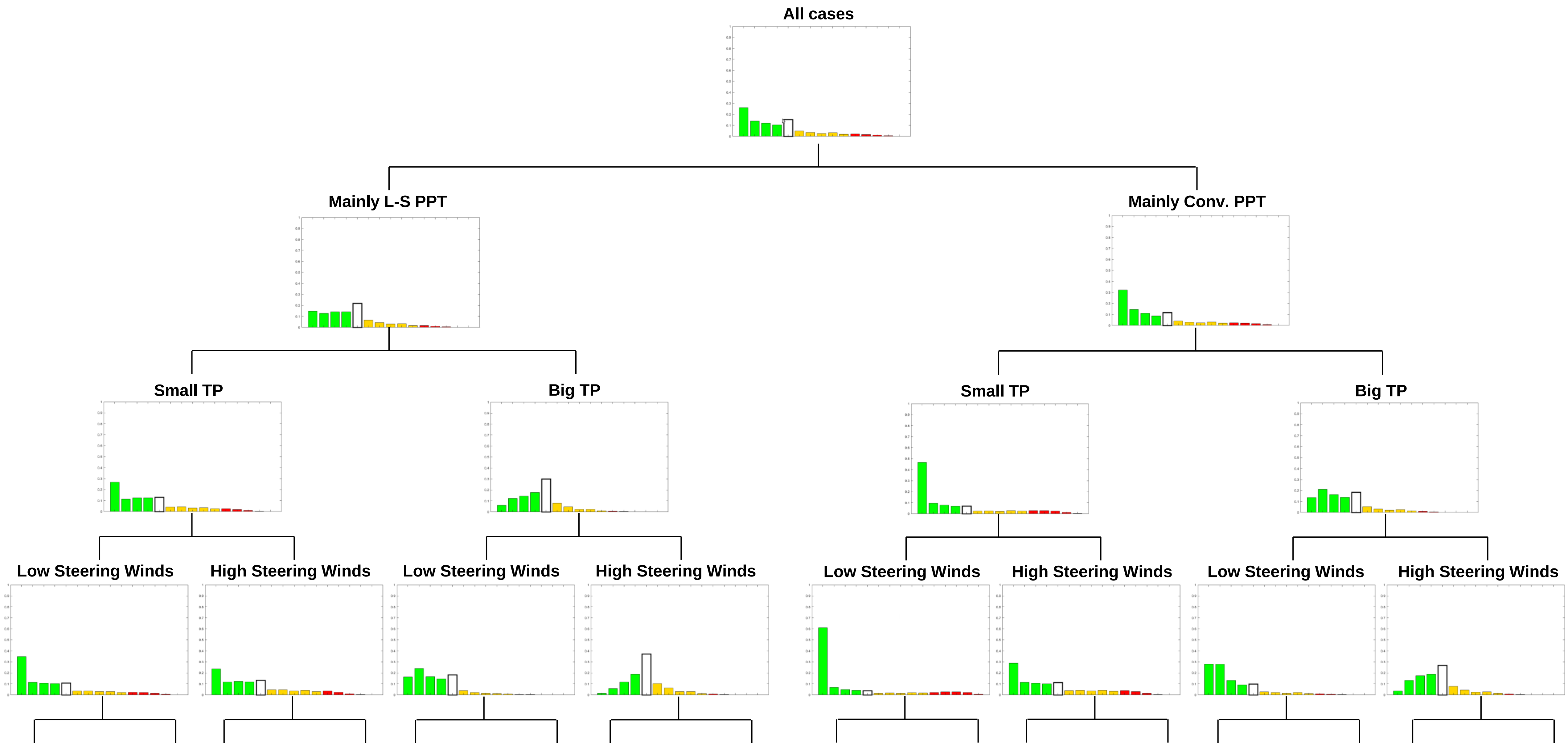
Predictors to create the WTs
(= geographical / solar / raw model / derived parameters)

Current pre-operational version

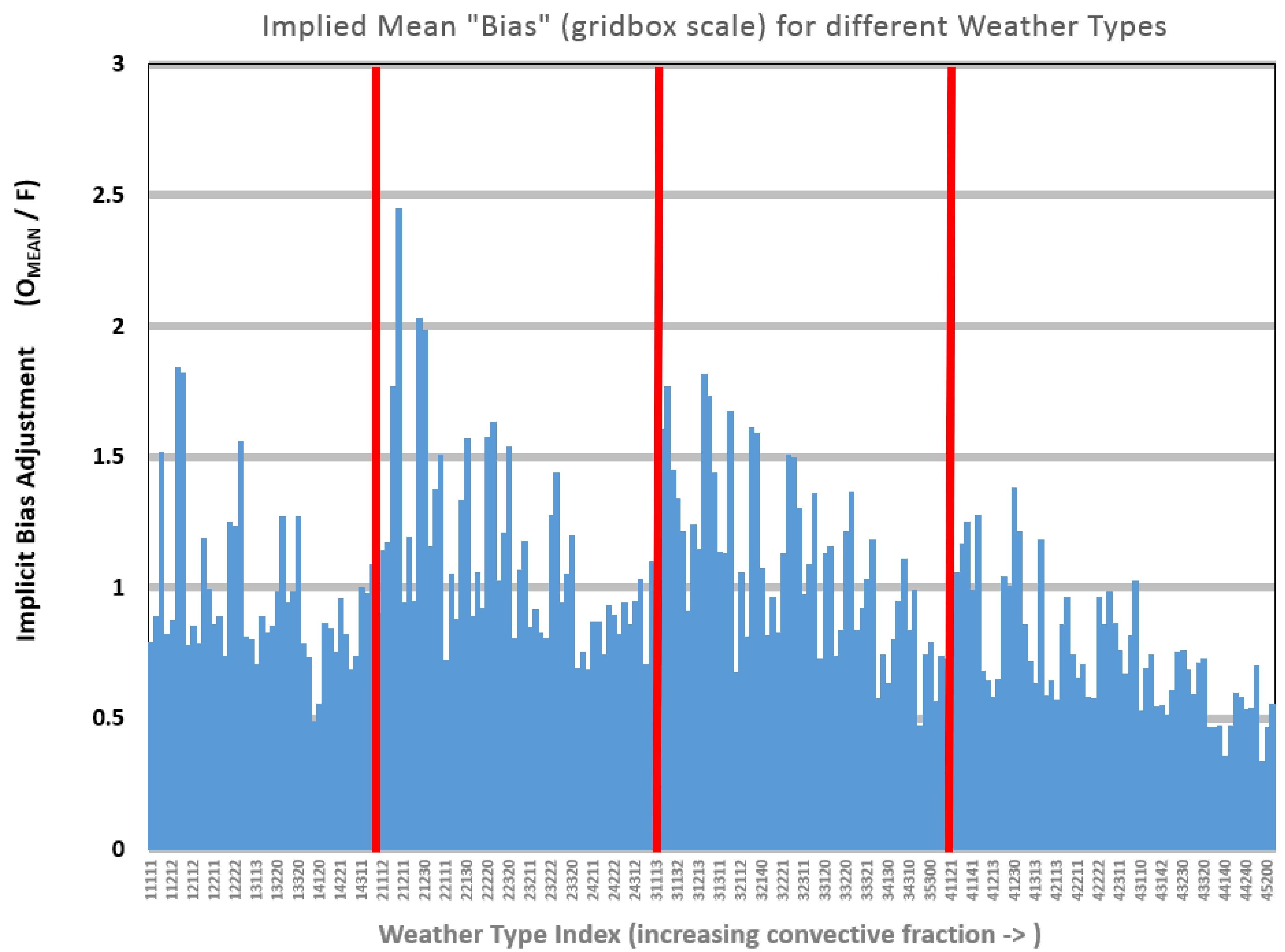
- Convective Precipitation Fraction
- Total precipitation forecast
- Mean speed (in period) of steering winds at 700 mbar
- Convective available potential energy
- Clear Sky solar radiation, 24h accumulation

Future Research

- Complex orographic areas
- Coastal areas
- Rural and Urban areas
- Day, night, polar night
- Cloud cover
- Boundary layer depth
- Etc ….



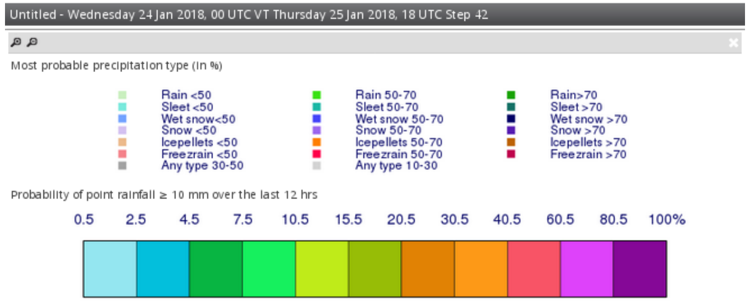
All cases
Mainly L-S PPT
Mainly Conv. PPT
Small TP
Big TP
Small TP
Big TP
Low Steering Winds
High Steering Winds
Low Steering Winds
High Steering Winds
Low Steering Winds
High Steering Winds
Low Steering Winds
High Steering Winds



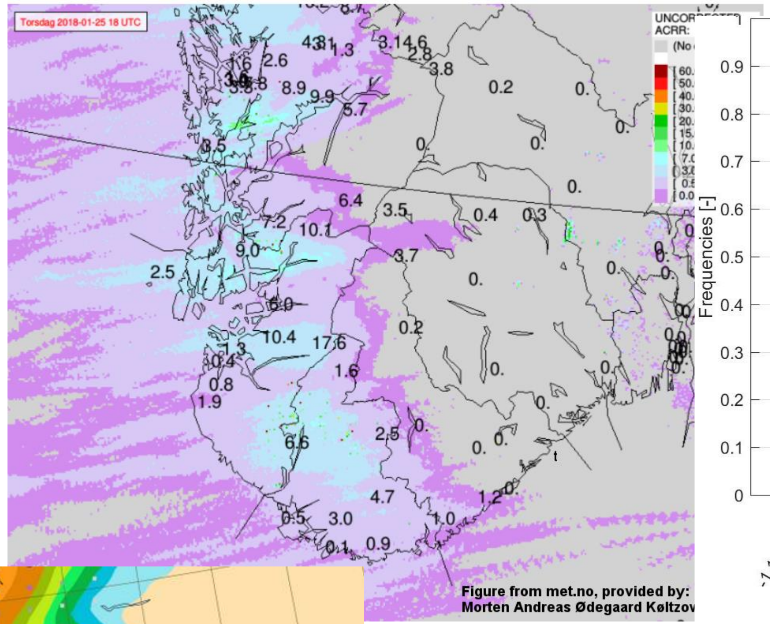
Implied Mean "Bias" (gridbox scale) for different Weather Types
Implicit Bias Adjustment (OMEAN / F)
3
2.5
2
1.5
1
0.5
0
Weather Type Index (increasing convective fraction ->)

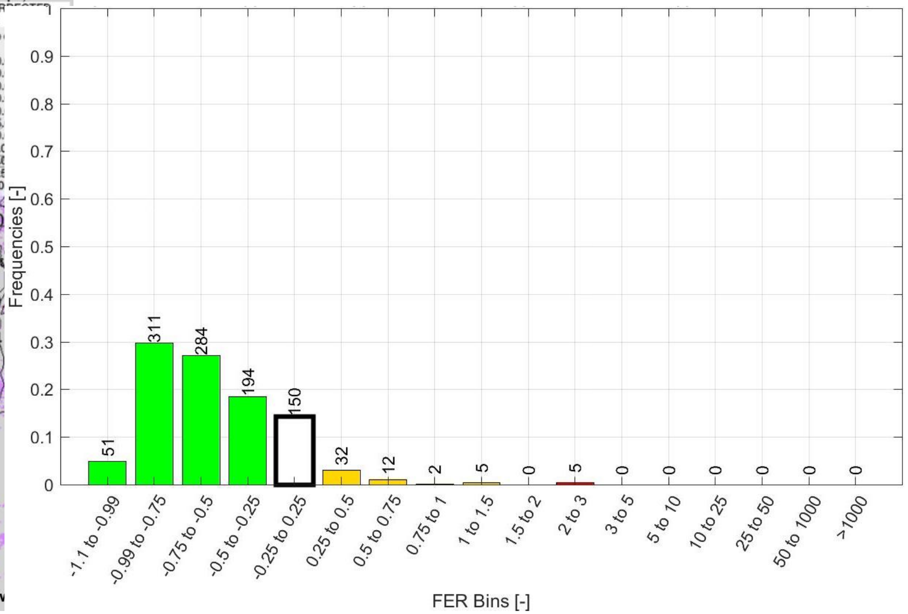
Example

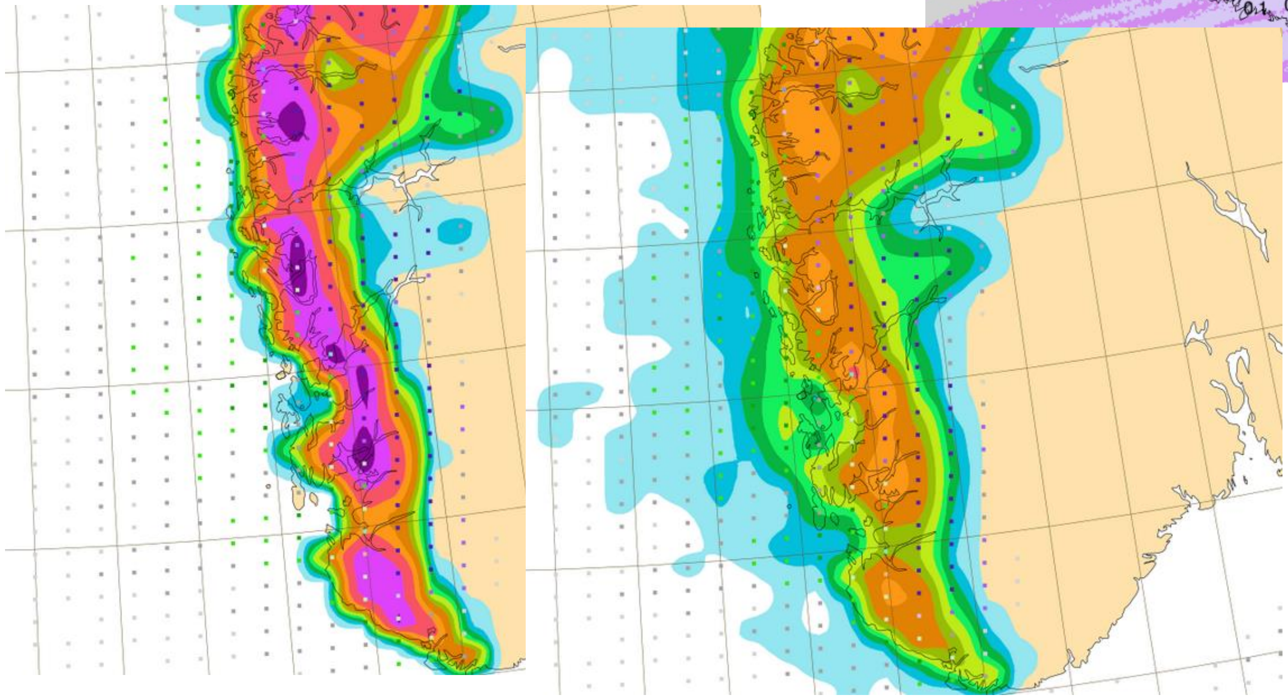
Norway, 25/01/2018, 00 UTC



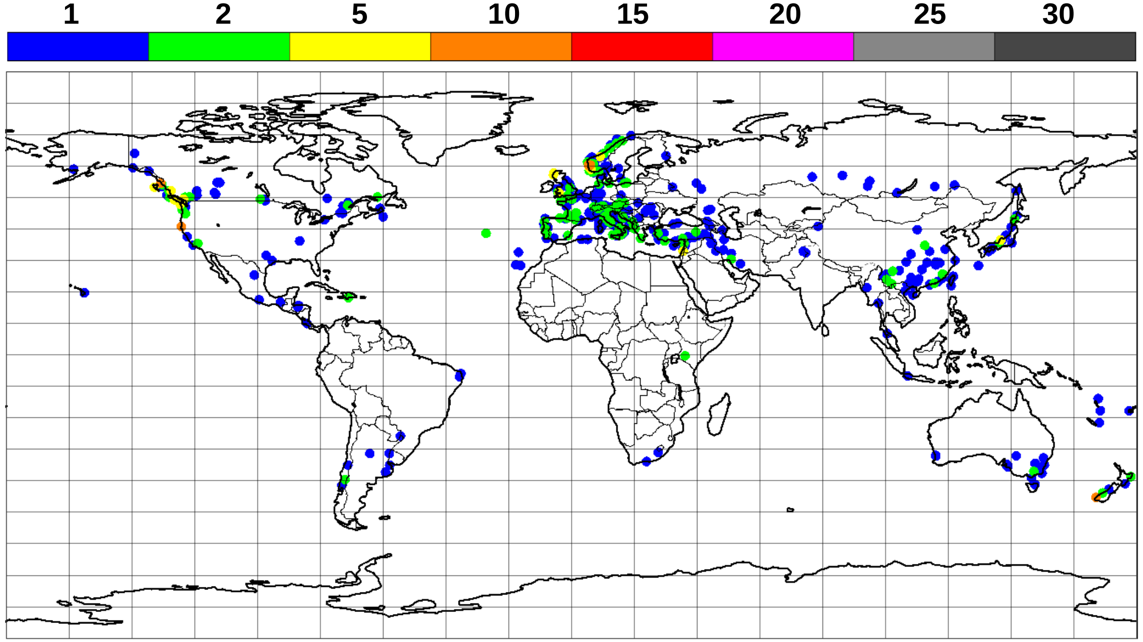
12hr_accumulated_precip_20180125_18UTC.png







Number of instances per Weather Type



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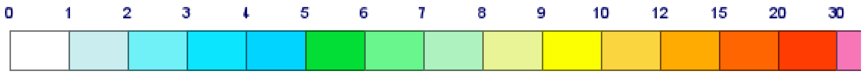
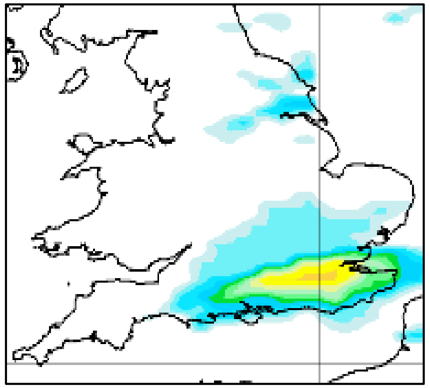
Example

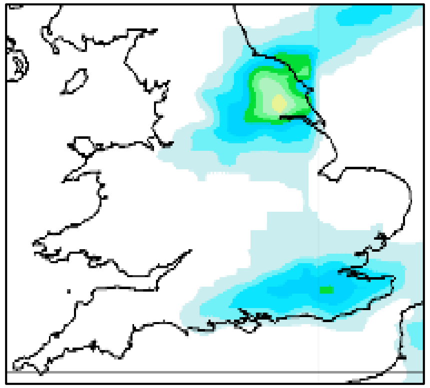
UK, 6 July 2017, 06-18 UTC



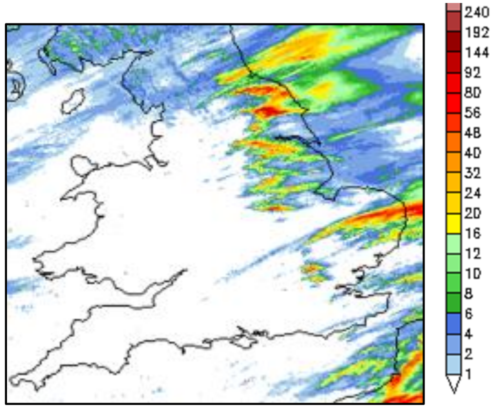
Raw Ensemble

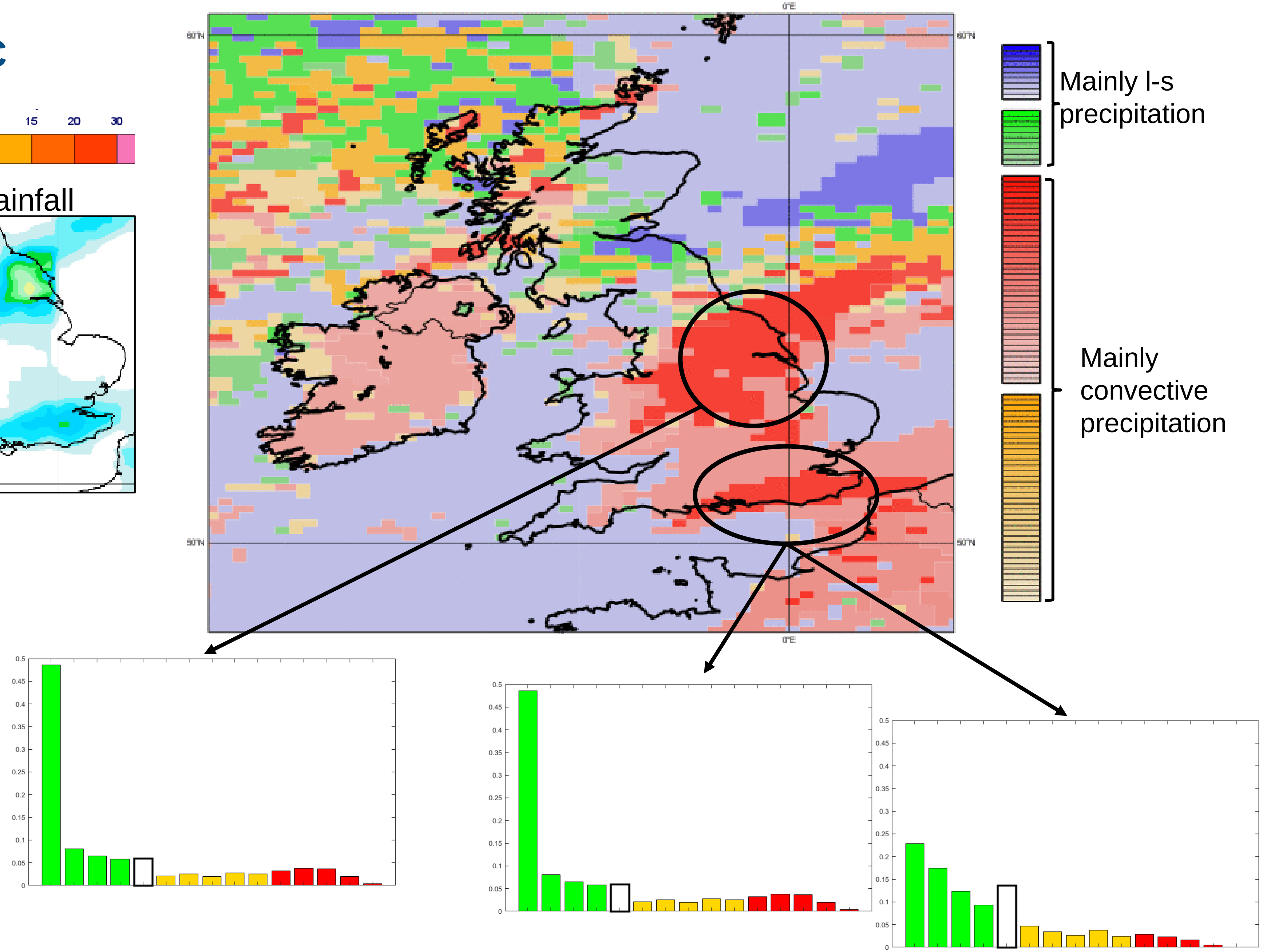


Point-Rainfall



Radar





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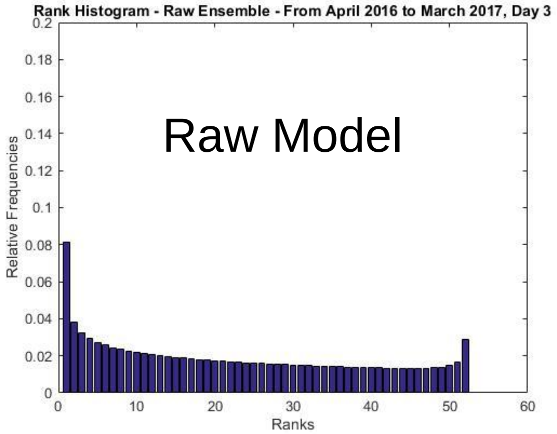
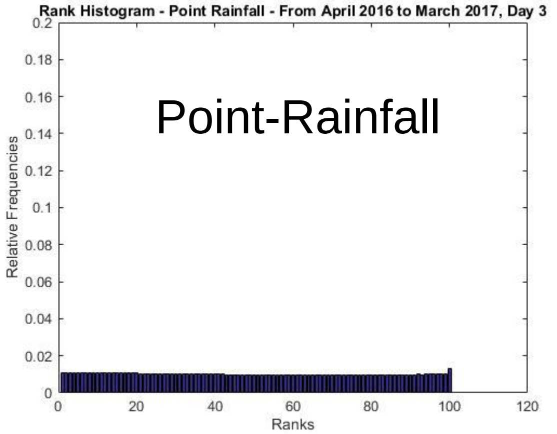
VERIFICATION

Long-term verification (April 2016 – March 2017) & different lead times (Day 1, 3, 5)

Reliability (Rank Histograms)





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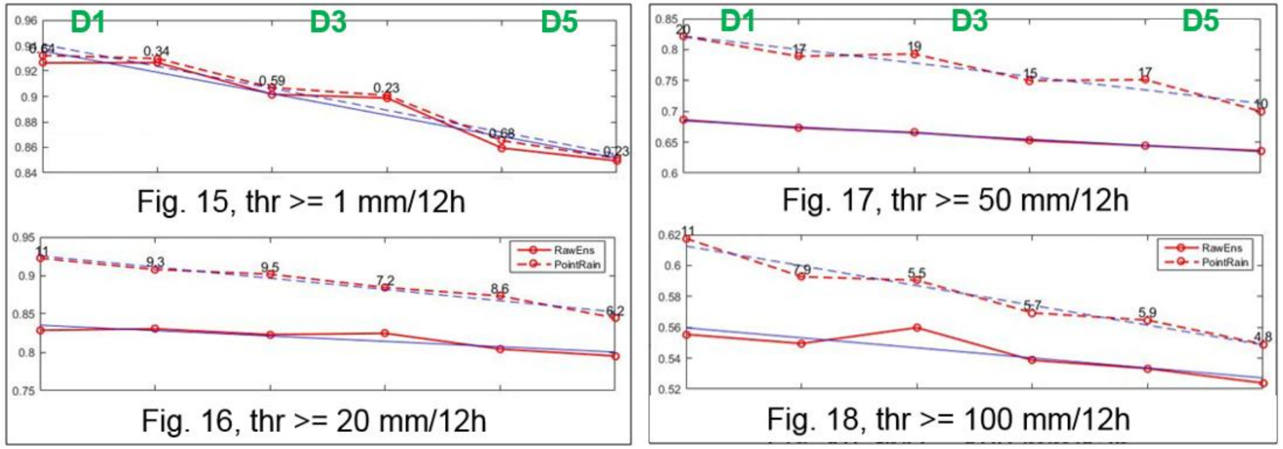
Resolution Component (Area under the ROC curve)

Raw Model Point-Rainfall



By this metric, for “large” totals the Point Rain product is ~ as skilful at day 5 as the Raw ENS is at day 1

=> Much better probabilistic flash flood predictions