

Introduction

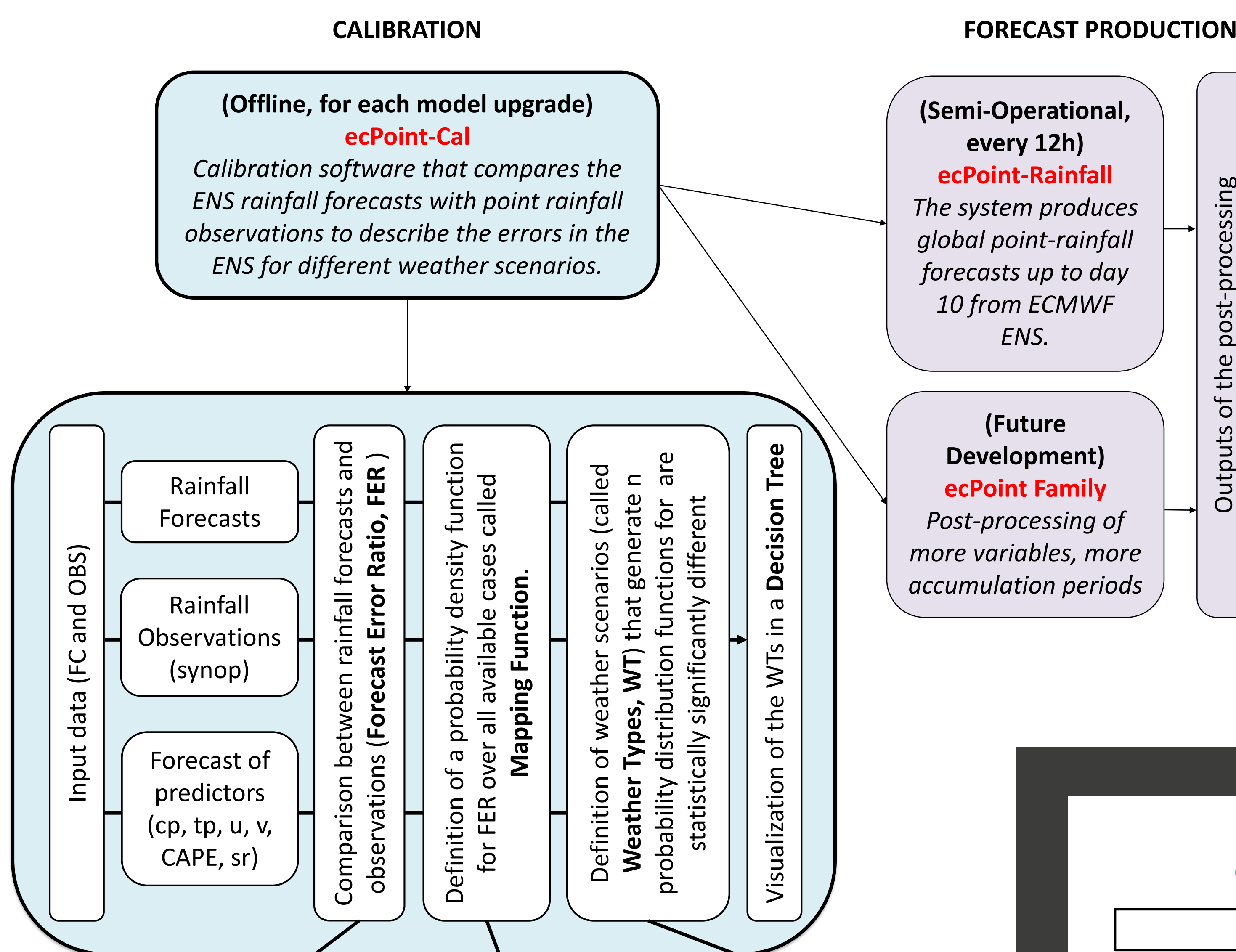
Flash floods are one of the most devastating natural hazards due to the economic/human losses that they can cause. Therefore, better and earlier warnings are vital.

High resolution hydro-meteorological models or radar nowcasting are classical approaches in flash flood warning systems. However, this techniques cannot offer global coverage, and they commonly reduce warning lead times to few hours.

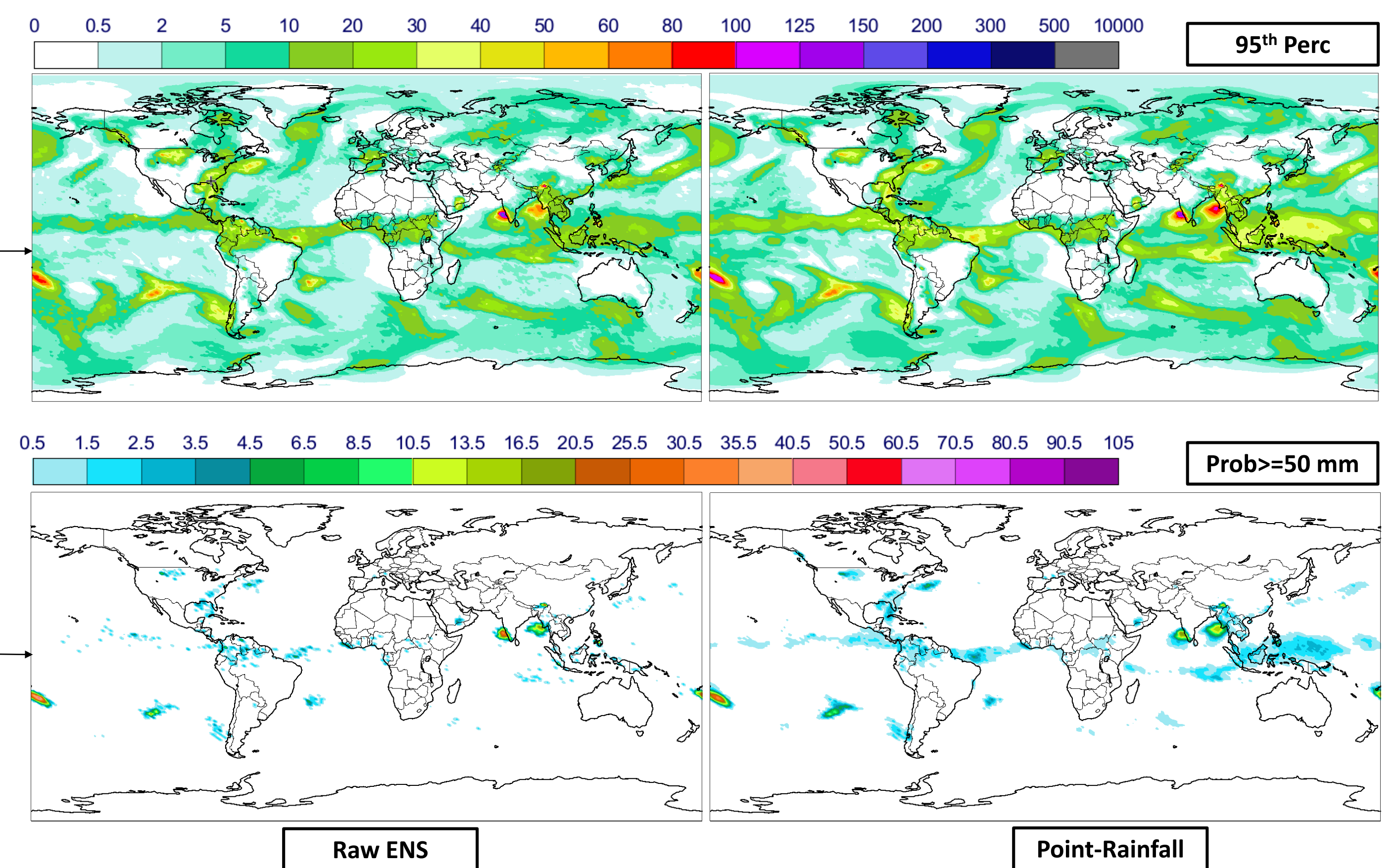
Global numerical weather prediction models are not used much because they tend to underestimate very localized heavy rainfall.

ECMWF has developed a novel statistical post-processing technique that looks at physical processes that explain errors in its global ENSEMBLE rainfall forecasts when verified against point observations to **anticipate sub-grid variability** and **improve biases**. It provides **more reliable and skillful probabilistic rainfall forecasts at point scale** that can **better detects and locates localized extreme rainfall totals**. The post-processed rainfall forecasts provide **warnings up to day 10**. Therefore, this new product has the potential to be used as a **complementary tool to detect areas of high flash flood risk**.

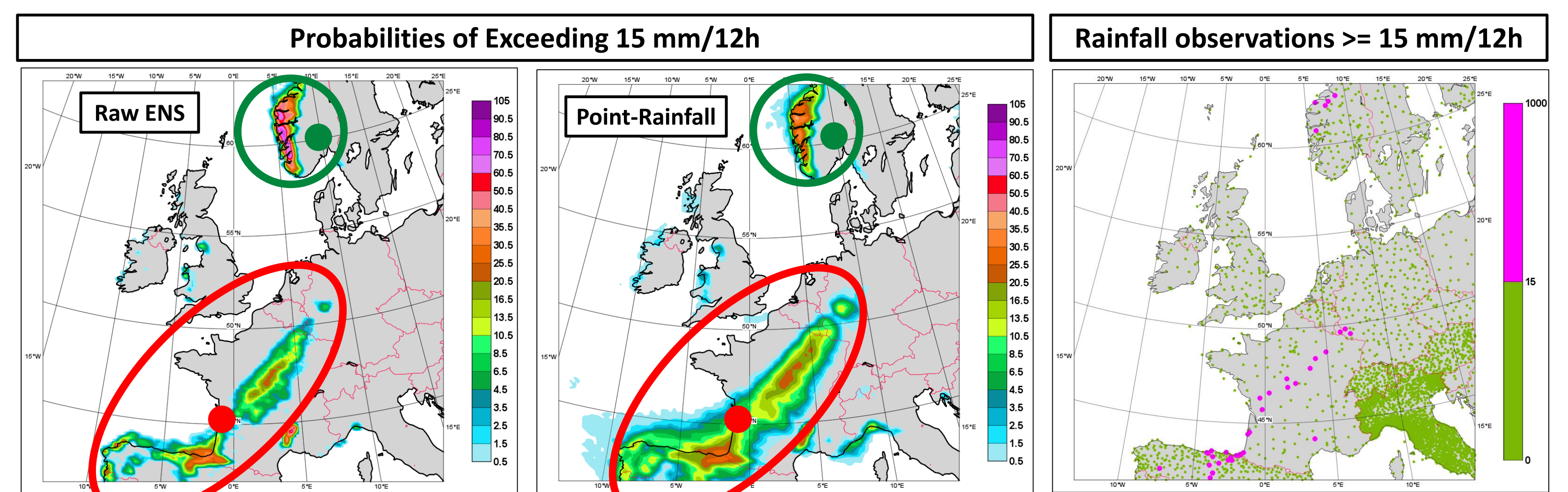
Post-Processing Workflow



Post-Processing Outputs



Case Study (12 h accumulated rainfall, Day 3 forecast, VT 25 January 2018)

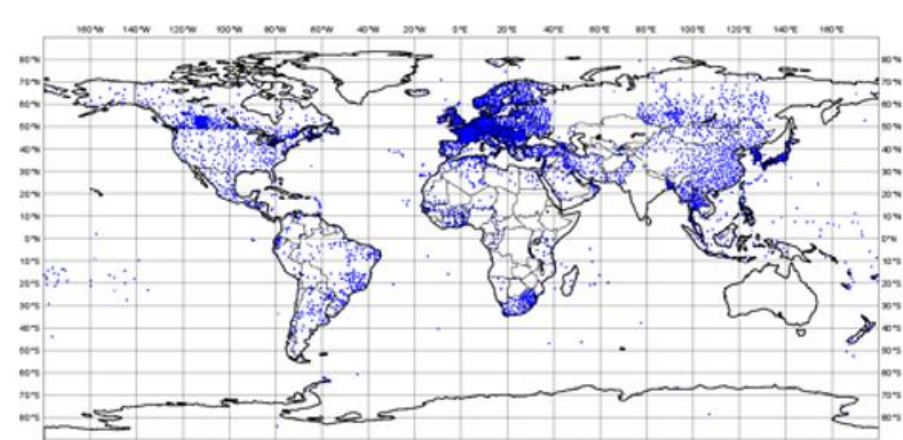


Benefits for users

- Better probabilistic rainfall forecasts for individual sites on average (larger spread than the raw ENS, which is under-dispersed for sites)
- Bias correction of the PDF mean for the meteorological/geographical situation (useful as hydrological forecast input)
- The probability distribution has a longer "wet tail" in most situations
  - extremes predicted in convective situations can be much higher (very low probability)
  - extremes very much better than the raw ENS (see verification)
- Much more reliable forecasts of zero rainfall (notably in convective situations)
- To overcome the difficulty in traditional post-processing systems of having insufficient training data in the region(s) of interest – remote site data usage is intrinsic to the methodology, so:
  - (i) long training periods are not needed, and (ii) forecasts can be produced for everywhere in the world, even for places where rainfall observations are not available.

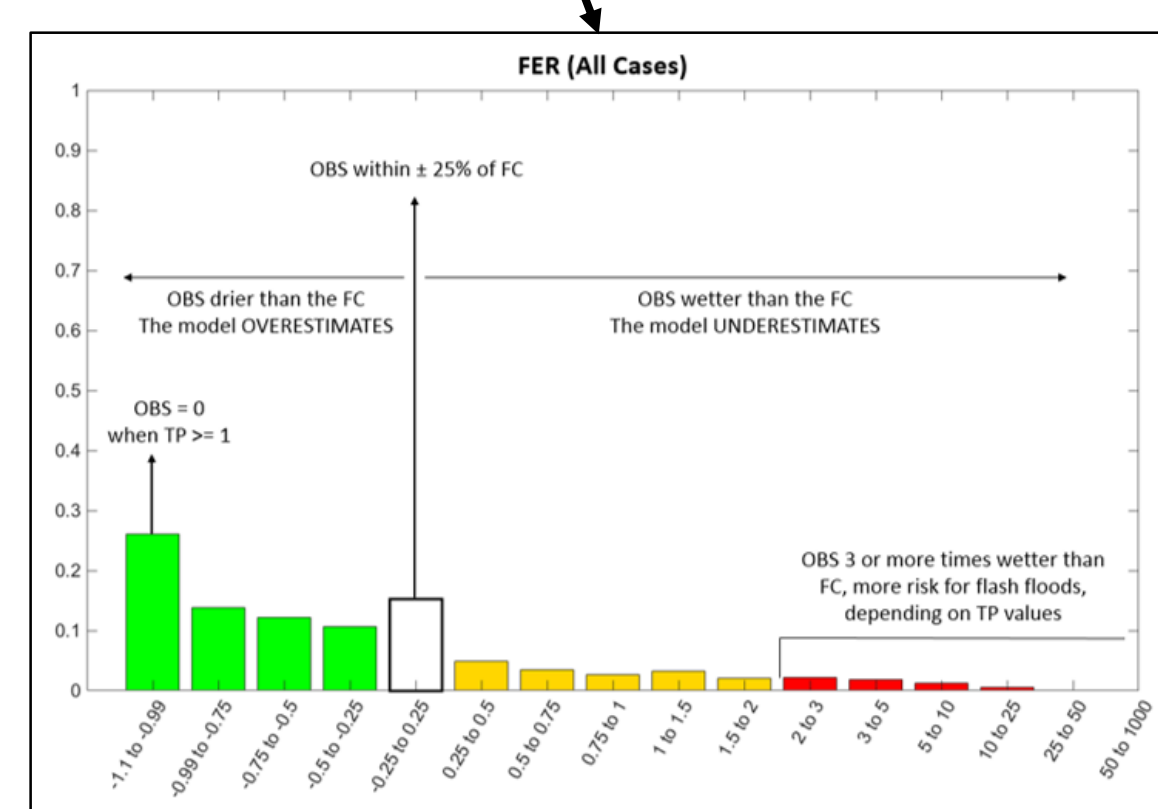
**What does FER represent?**  
 Over all available cases, it compares synop observations for rainfall ( $O_{point}$ ) and short range rainfall forecasts (typically for less than  $t+48$ , and  $F_{gridCAL} > 1mm/period$ )

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

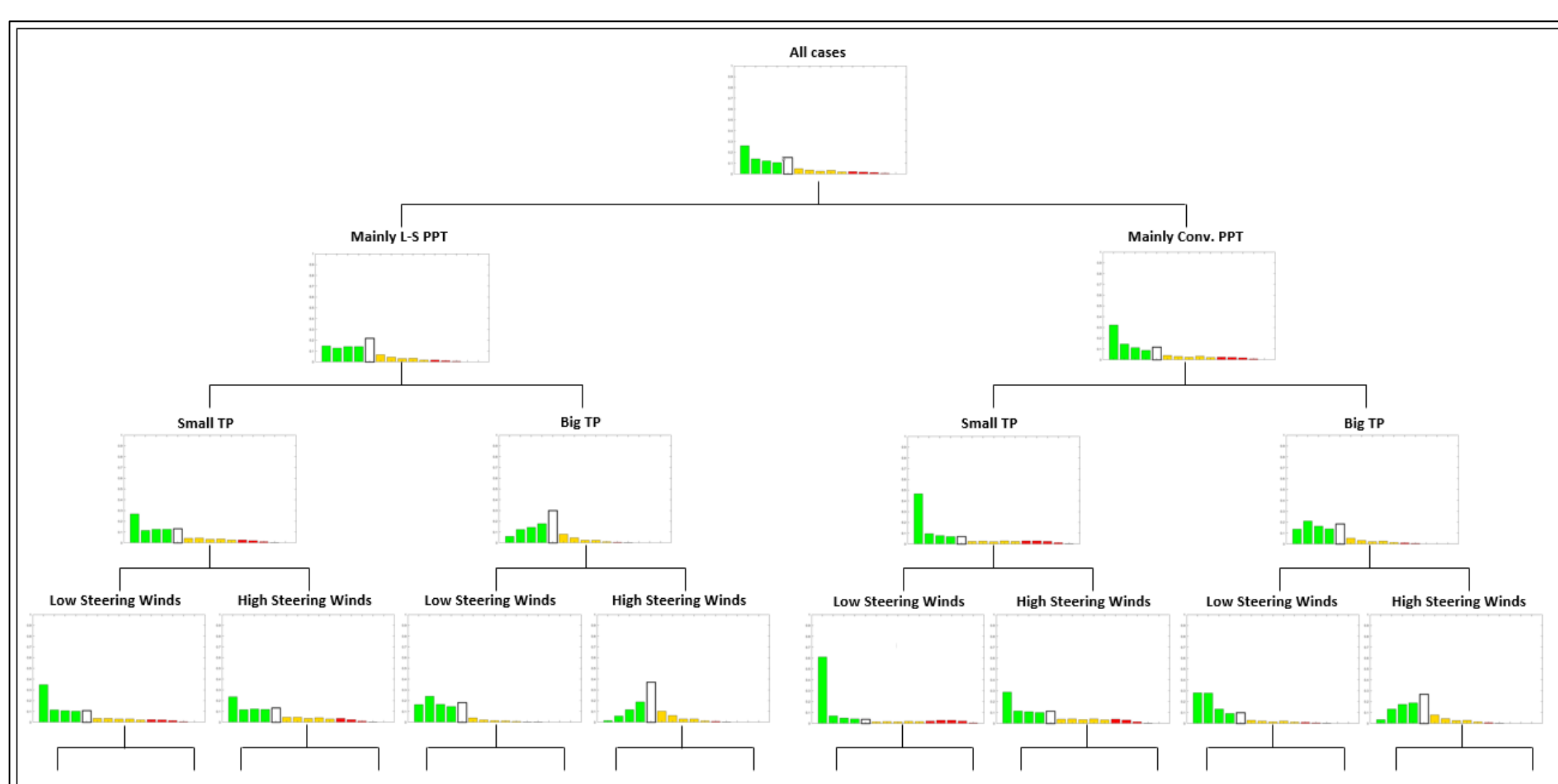


12-hourly synop rainfall observations available around the world. It can be noticed the non-homogeneous spatial distribution of the observations around the world. This non-homogeneity can be seen as well in the temporal scale (not shown).

A 2-sided Kolmogorov-Smirnov test and similarity scores for different distribution attributes are computed to determine iteratively the break points for each WT. Expert elicitation is here applied to define the hierarchy under which the predictors will be considered and refine the break points.



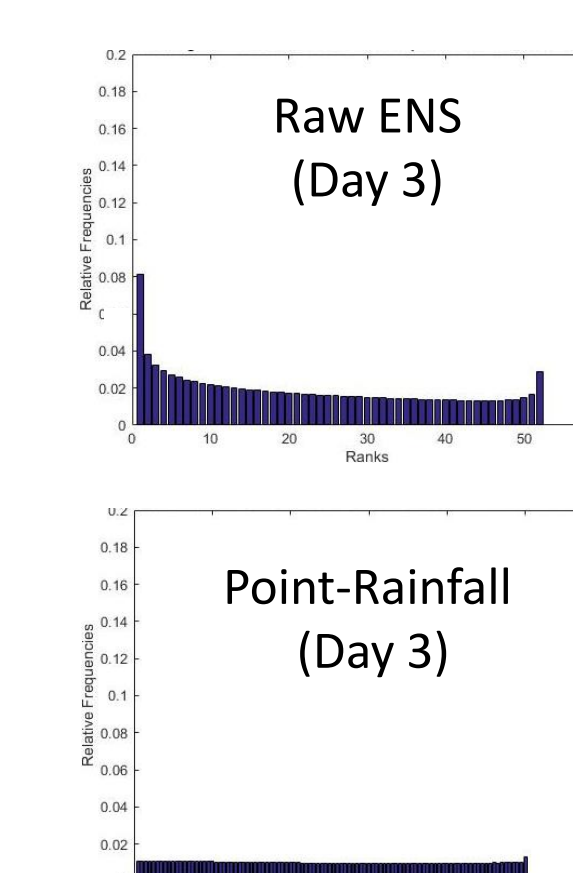
Partial visualization of the WTs as a decision tree



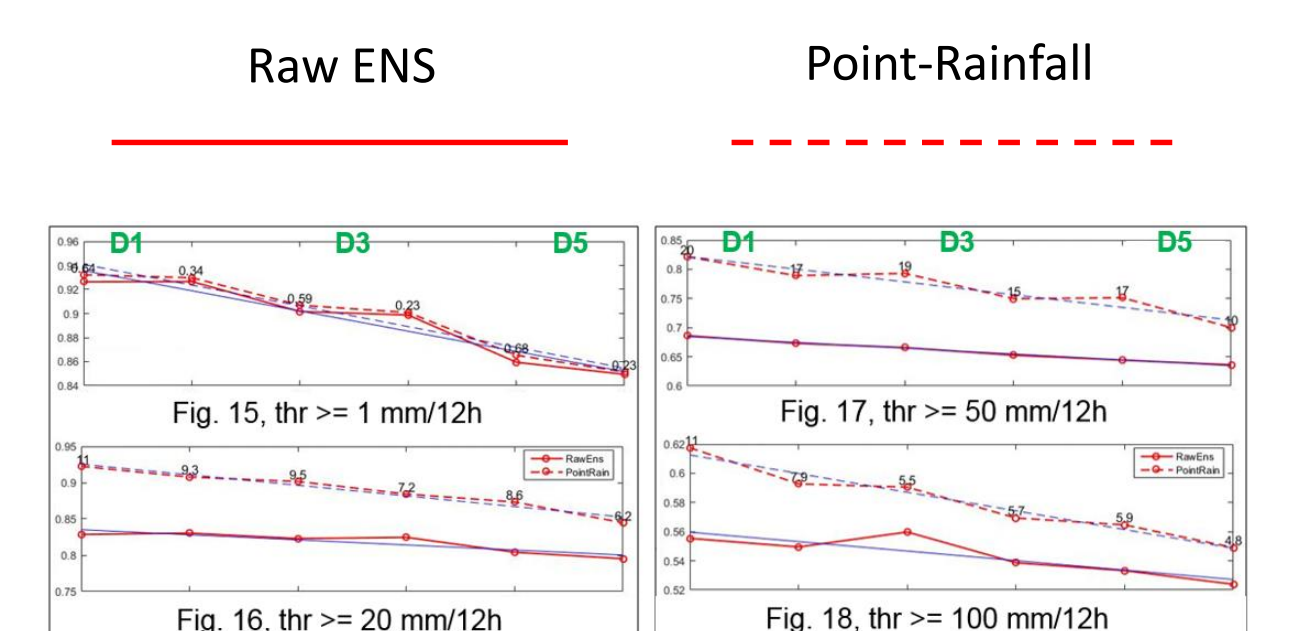
The efficacy/utility of this procedure relies on the ability to define multiple mapping functions for n physically and significant different WTs. Indeed, this allows one to anticipate weather-dependant variability within the model grid-box, and also weather-dependant model biases in grid-box average rainfall.

Long-Term Verification (from April 2016 to March 2017, up to day 5)

Reliability Rank Histograms



Resolution Component Area under the ROC curve



By the "area under the ROC curve" metric, for large totals the Point-Rainfall is roughly as skilful at day 5 as the Raw ENS at day 1