Verification of clustering methods for hydrological ensemble forecasts

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HEPEX Tenth Anniversary Workshop

24-26th June 2014, Maryland, USA

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Outline

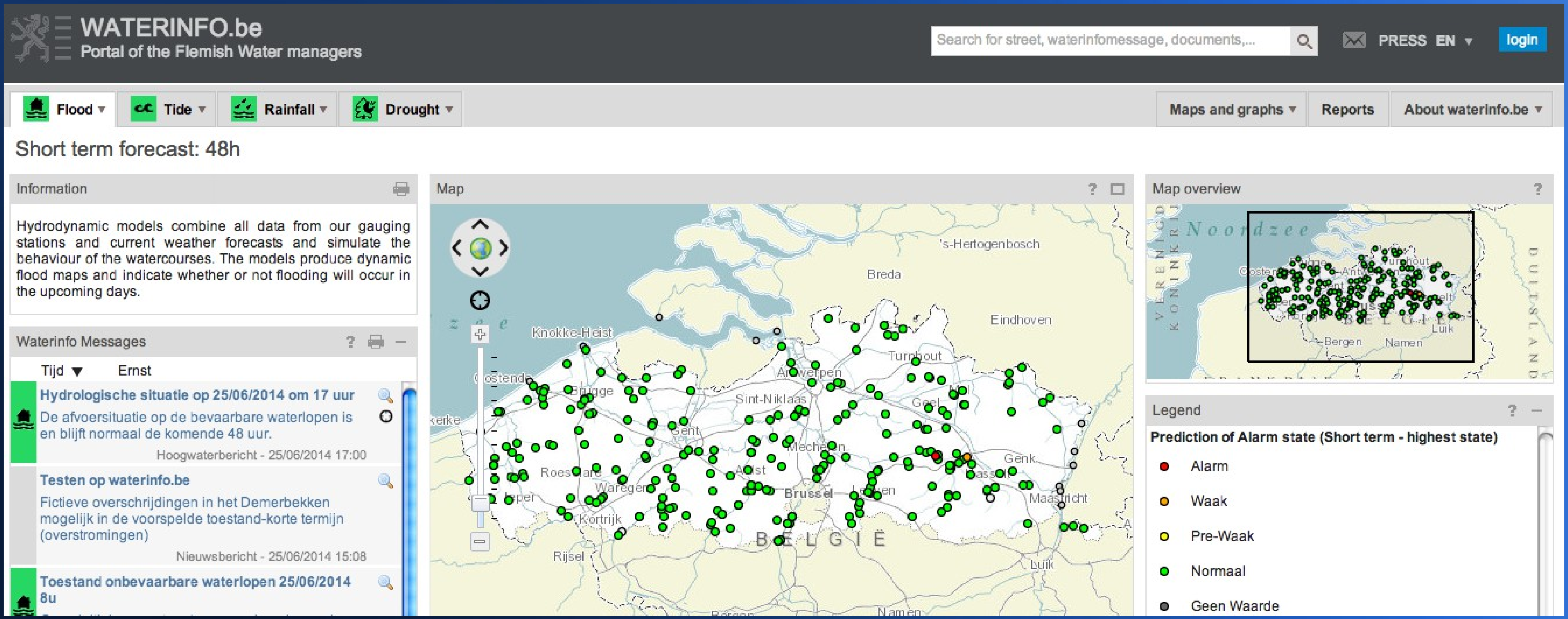
- Introduction.
- Clustering & representative ensembles.
- Verification.
- Hydrological verification.
- Conclusions.

Introduction

- Project with Flemish environment agency (VMM, end user), Royal Meteorological Institute Belgium (RMI) and International Marine and Dredging Comsultants (IMDC).
- Aim: reduce an ensemble of precipitation forecasts to a smaller set of “representative members” (scenarios) for use as input for the detailed hydraulic model used by VMM.
- ~50 → 5-10 ensemble members.

VMM

- Responsable for water management of Flemish non-navigable rivers. Website: WATERINFO.be



Introduction

- Our solution: **clustering algorithm.**
- Literature study of available methods.
- Development of new methods.
- Evaluation of some proposed methods, using GLAMEPS and ECMWF ENS ensembles.
- Verification for Dijle catchment (≈ 900 km^2) for two 1-month periods (winter and summer).

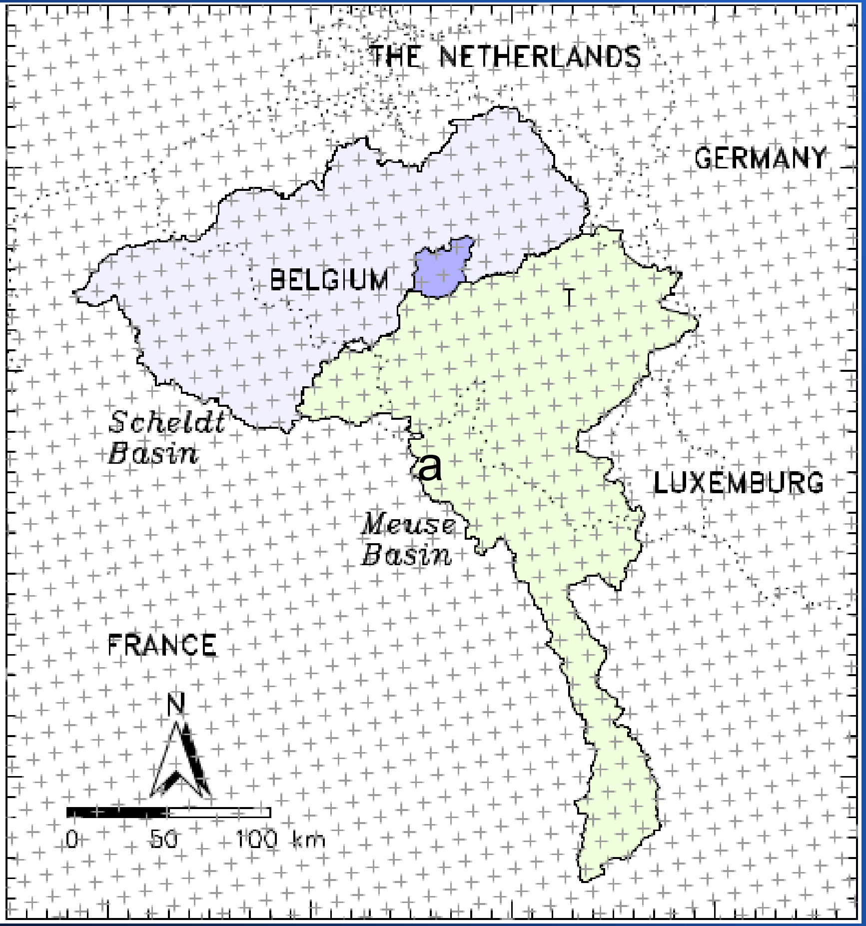
ECMWF ENS

- 51 member ensemble (global).
- Forecast range: 10 days, resolution ~30km (up to 14 days at ~50km resolution). N320 grid.
- Runs at 00 and 12 UTC.
- Singular vectors, stochastic physics perturbations, ensemble data assimilation.
- Postprocessing to be performed by end users.

GLAMEPS (v1), *www.glameps.org*

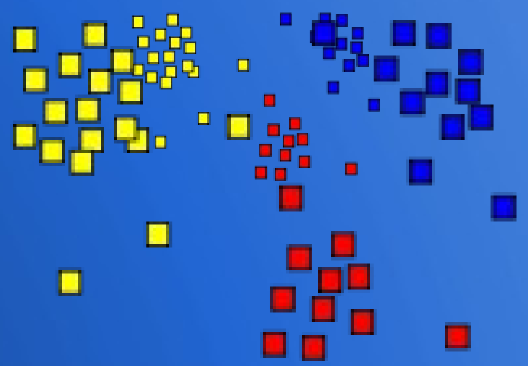
- 54 limited area ensemble members:
  - ECMWF ENS, ECMWF DET (downscaled),
  - AladEPS, HirEPS-K, HirEPS-S.
- Forecast range: 54 hours, ~11 km resolution.
- Runs at 06 and 18 UTC.
- Postprocessing with BMA.

GLAMEPS gridpoints, Dijle catchment



Clustering

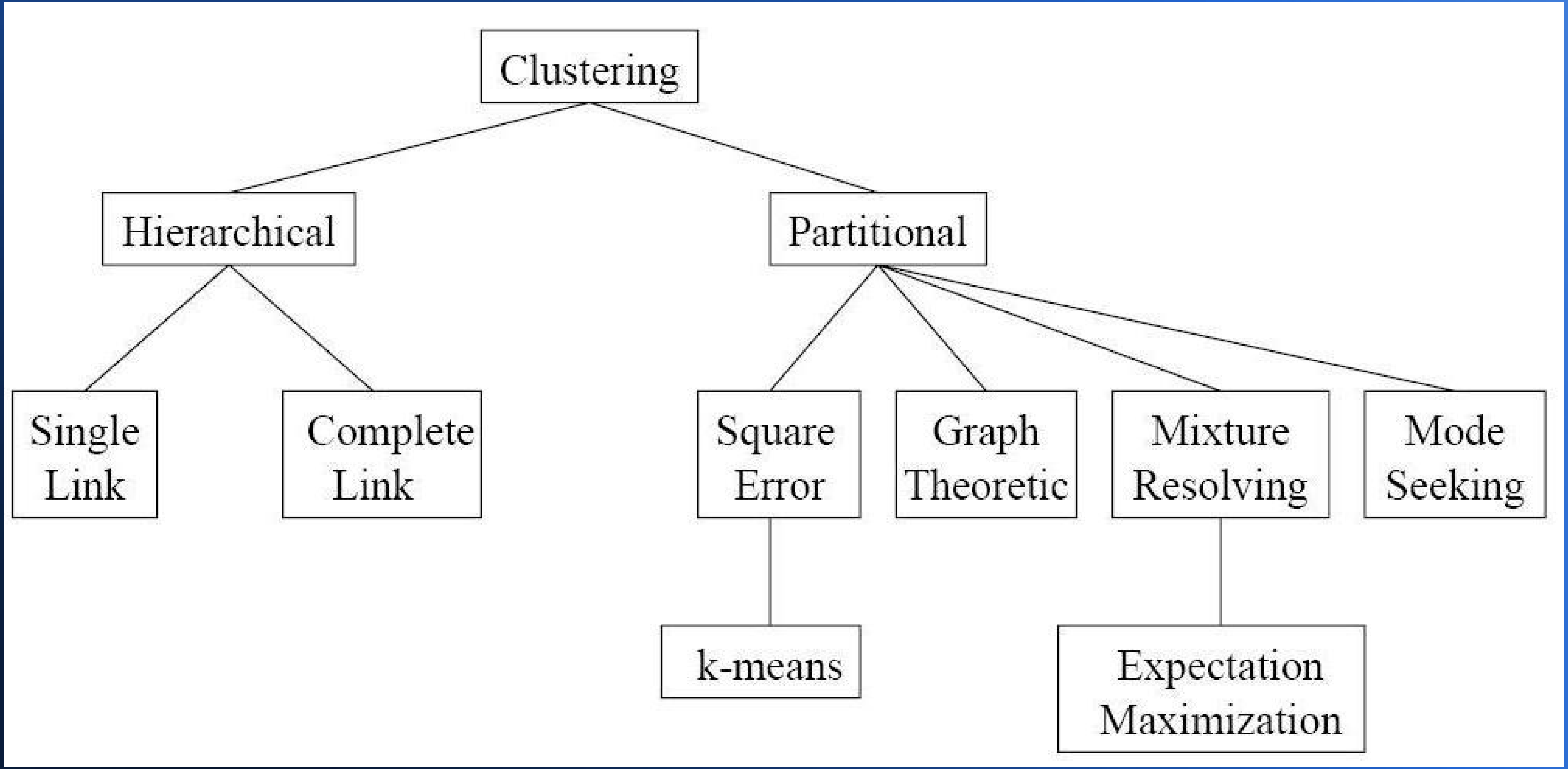
- Clustering: **partition objects** into clusters such that objects with similar characteristics are clustered together and dissimilar objects end up in different clusters.
- Form of **unsupervised learning**: little or no prior information on object classification.



Clustering

- Many different algorithms and applications.
- Main ingredient to define “similarity”: **distance measure** for n data vectors in K-dimensional space:
  - Euclidean
  - Karl-Pearson
  - “City block distance”, …
- Computation of n(n-1)/2 pairs of distances.

Clustering


Clustering
Hierarchical
Partitional
Single Link
Complete Link
Square Error
Graph Theoretic
Mixture Resolving
Mode Seeking
k-means
Expectation Maximization

Hierarchical clustering

- Partition objects into tree of nodes.
- Iterative procedure, object cannot change cluster once assigned.
  - Agglomerative: “bottom up”, start with n clusters, iterative merging of pairs.
  - Divisive: “top down”, start with 1 cluster and iteratively decompose (computationally expensive).
- After cluster assignment, methods allow to assign “most representative” members.

Partitioning clustering

- Non-hierarchical, objects can be re-assigned to new clusters during procedure.
- Number of clusters *k* chosen a priori.
- Most well-known algorithm: k-means.

Clustering in Meteorology

- Classify into weather regimes, climate zones,...
- Clustering of ensemble forecasts to generate representative members (RM) for downscaling:
  - Based on meteorological variables such as MSLP, wind speed, relative humidity,...
  - Typically at synoptic scale.
  - Example: COSMO-LEPS (Marsigli et al, 2005).
- Most used method: hierarchical clustering.

Clustering in Meteorology

Problems/issues for our application

- Clustering at synoptic scale not always suitable for clustering at local scale.
  - Small scale catchments.
  - We are only really interested in precipitation.
- Clustering should not select different ensemble members on different days → temporal consistency and avoidance of “double counting”

Our approach

- Main idea: use precipitation directly to classify, no other meteorological fields.
- Precipitation at k different lead times → clustering on k dimensional space.
- Sub-ensemble taken from full ensemble.
  - Classify into 5-10 clusters,
  - take RM from each cluster,
  - associate prob. weight according to cluster size.

Tested methods

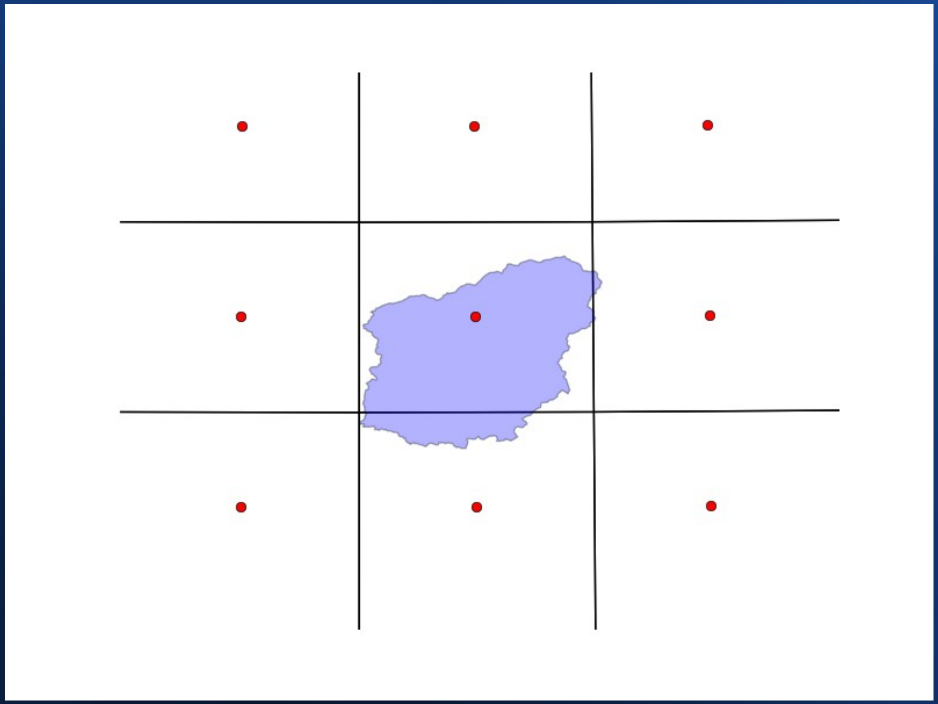
- Hierarchical agglomerative clustering method, based on Ward's method (e.g. *Wilks, 2004*).
- Our own developed “Optimal distance (OPT)” method, taking members that are the most different from each other (similar to *Sattler and Feddersen, 2005*).
- Quantiles of total accumulated precipitation.
- Quantile method that selects using “most active period” (bin with most precipitation).

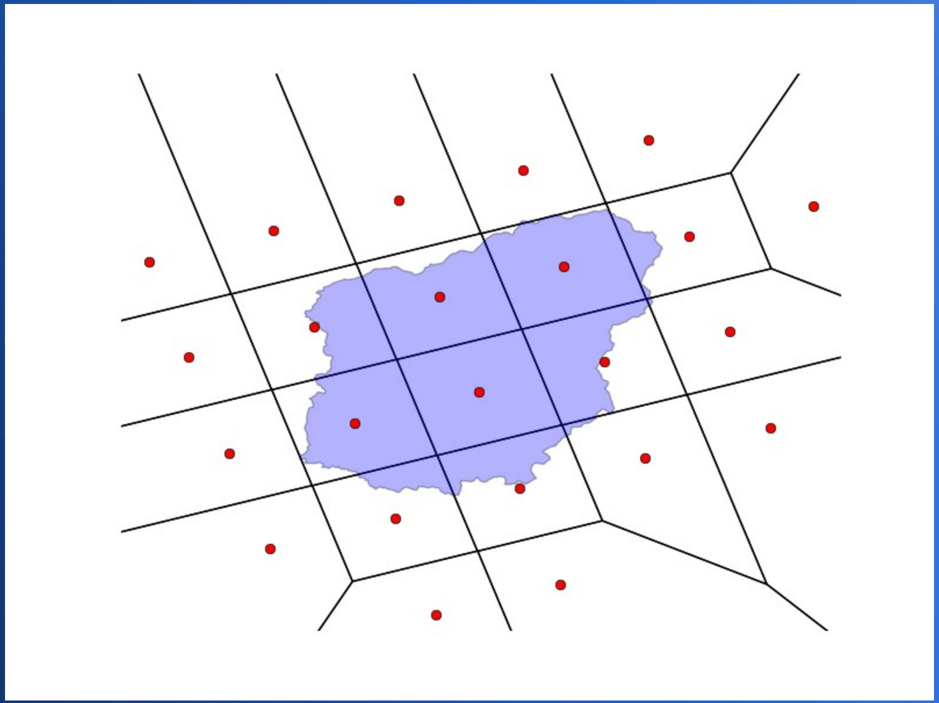
Verification setup

- Verification periods:
  - 1 month during summer 2012,
  - 1 month during winter 2012-2013.

  → GLAMEPS v1 available
- Comparison of observed areal precipitation with full ensemble forecast and sub-ensemble with representative members.
- Comparison of a hydrological model forced with full ensemble vs. forcing with sub-ensemble.
- Performance evaluation: visual, probabilistic scores.

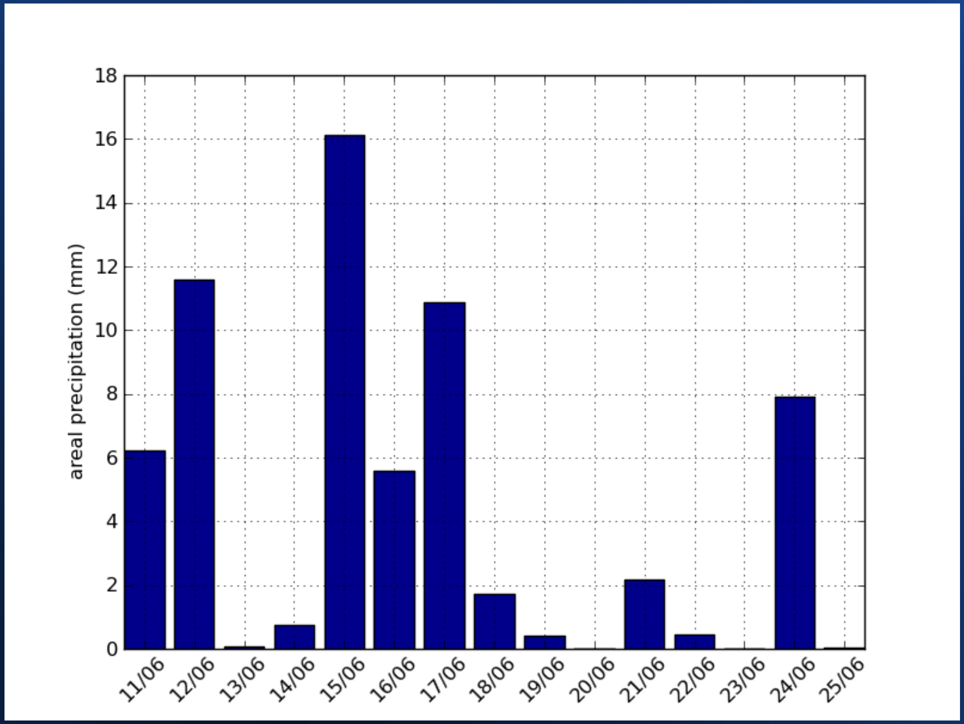
Dijle catchment & ENS/GLAMEPS gridpoints

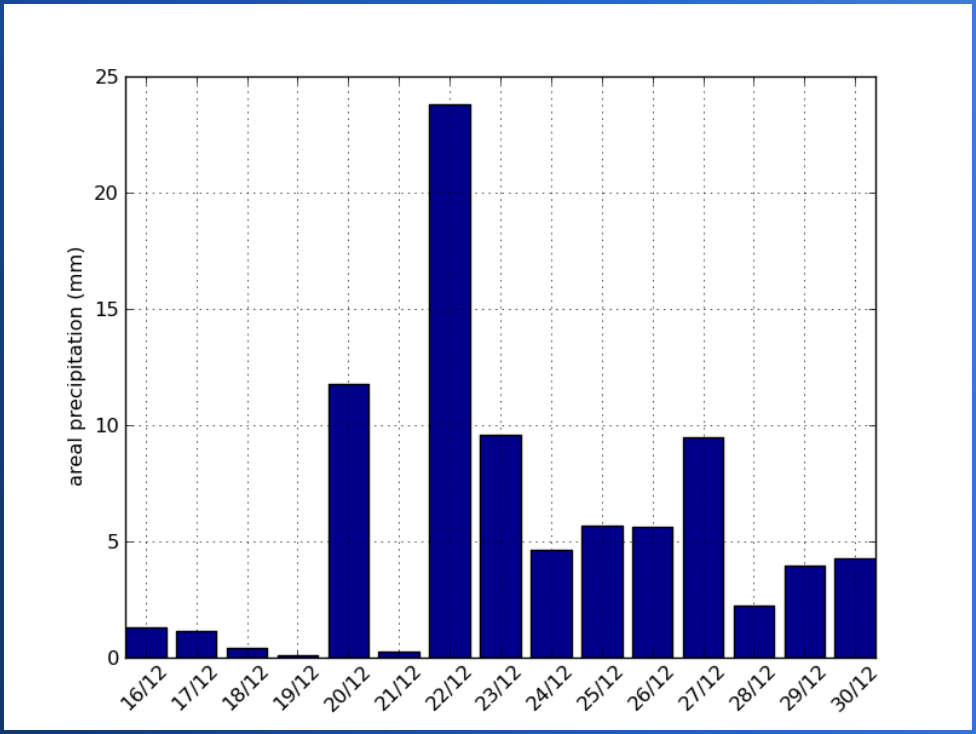




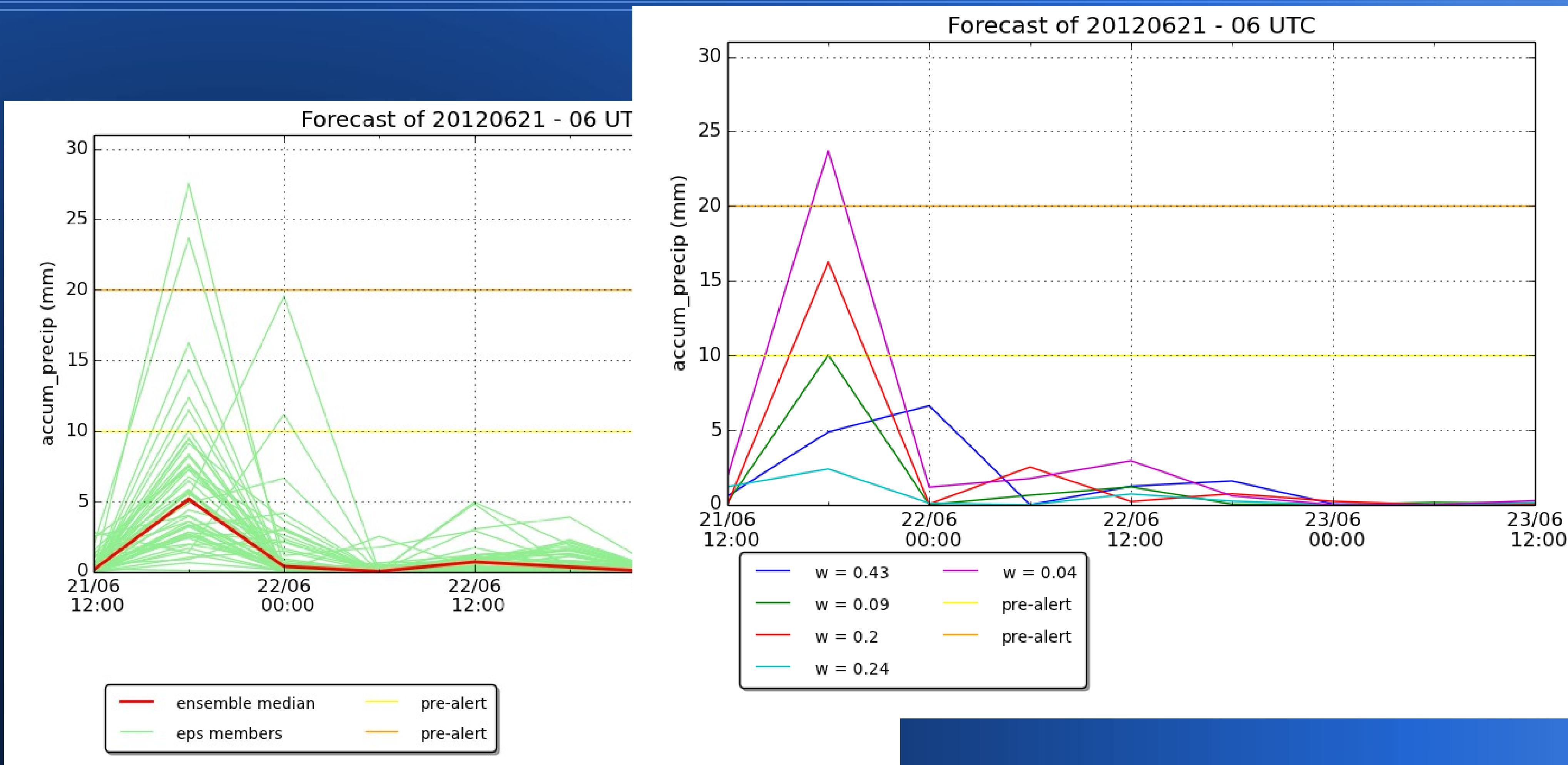
Verification

Dijle: observed areal precipitation for two test cases. Summer 2012 (left), winter 2012 (right).

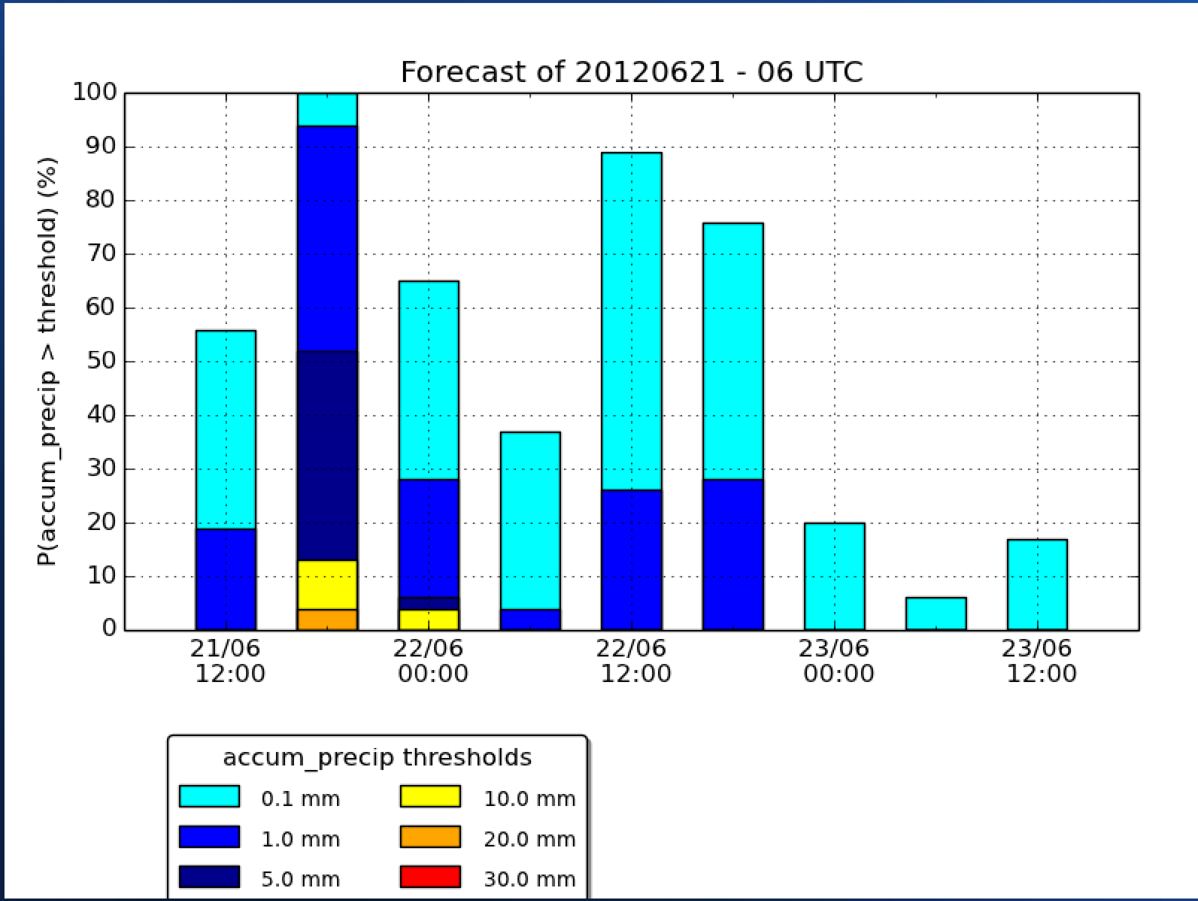




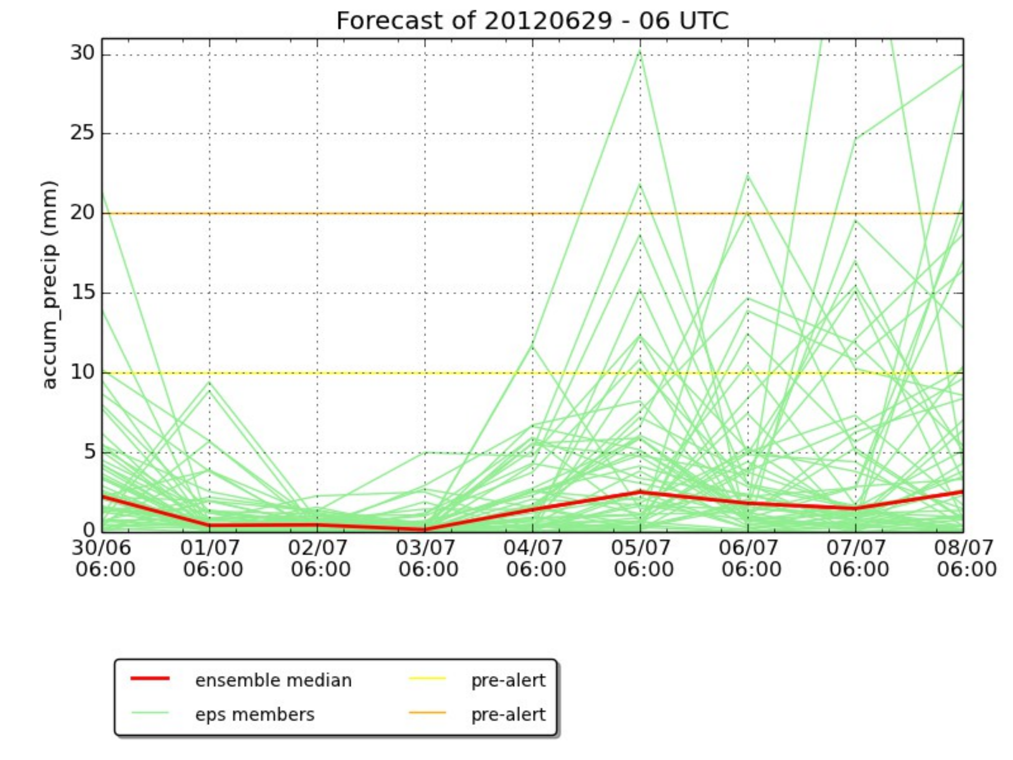
Verification example, GLAMEPS, hierarchical method

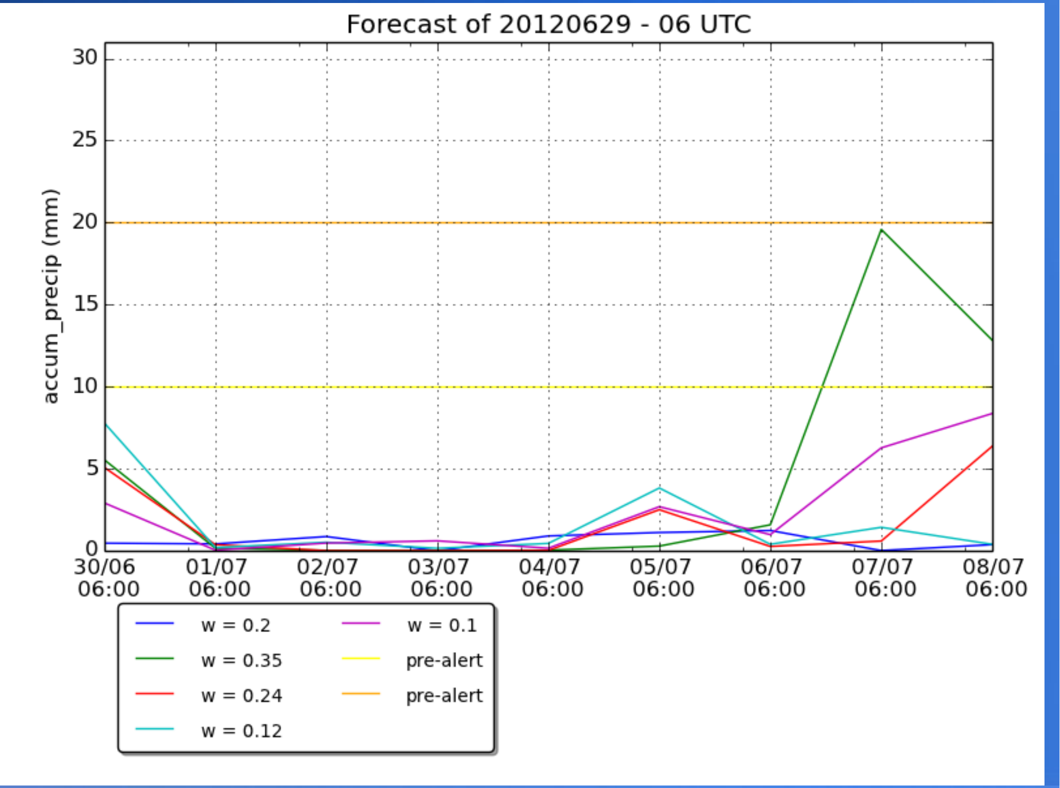


Probability plot using 5-member ensemble plus weights



Verification example, ECMWF ENS, hierarchical method

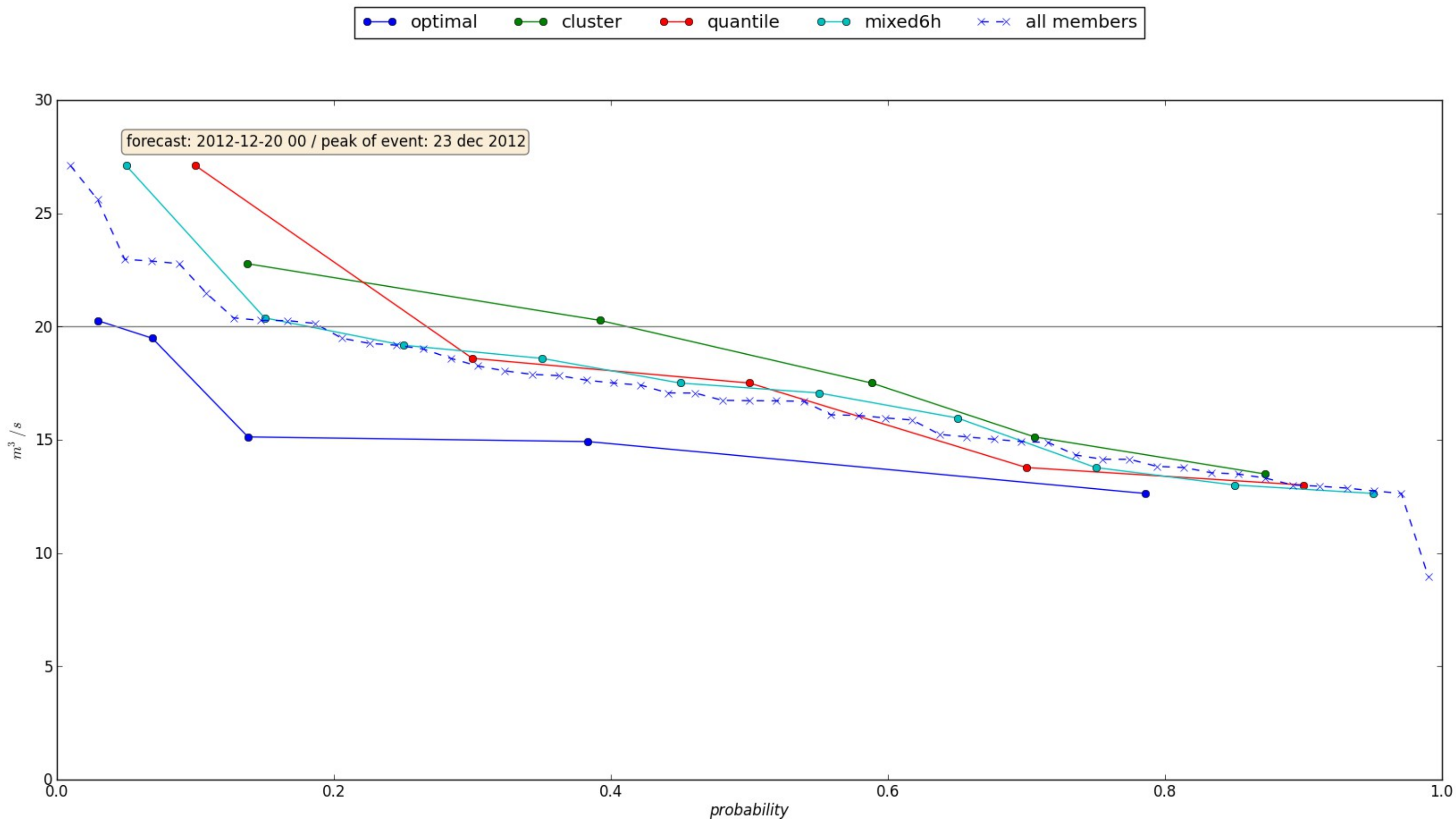




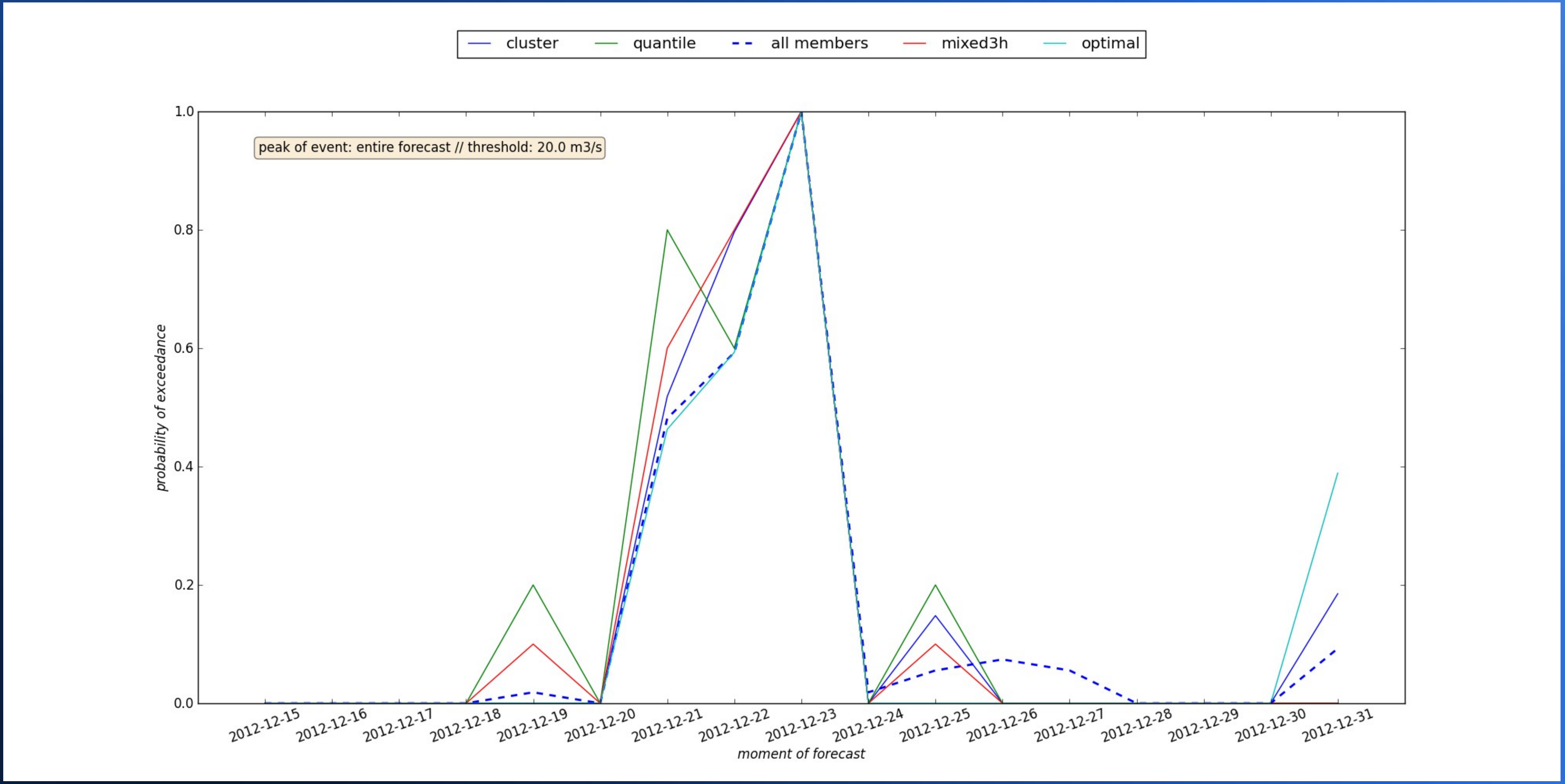
Hydrological Verification

- Complete GLAMEPS and ENS precip ensembles used as input for conceptual hydrological model.
- Sub-ensembles generated by our main 4 clustering methods with "best" parameter choices tested.
- Evaluation by comparison with full ensemble:
  - Peakflow probability distribution,
  - Probability of exceedance for thresholds.

Hydrological verification example: peakflow probability



Hydrological verification example: probility of exceedance



Some Conclusions

- All methods are “competitive”, there is not one that clearly stands out.
- Single peaks usually included in cluster, multiple peaks can be missed in sub-ensemble.
- Quantile method works quite well (CRPS score), and very simple to implement.
- Going from 5 to 10 members gives a large improvement, and is recommended if possible.

Further investigation & Work in progress

- Test clustering on more catchments and longer time period.
- Use of distance measure taking spatial structure into account.
- More detailed investigation of quantile method with selection of “active precipitation periods” (accumulation time, dependance on forecast range,...).

Questions?