Meteorologisk institutt
met.no

Statistical calibration of precipitation ensembles

John Bjørnar Bremnes

Overview of statistical methods

A. Transformation of ensemble members individually
   - *n* members $\Rightarrow$ *n* new members
   - No theoretical foundation for calibration

B. Calibration of complete ensemble simultaneously
   - Statistical models $\Rightarrow$ good theoretical foundation

Note

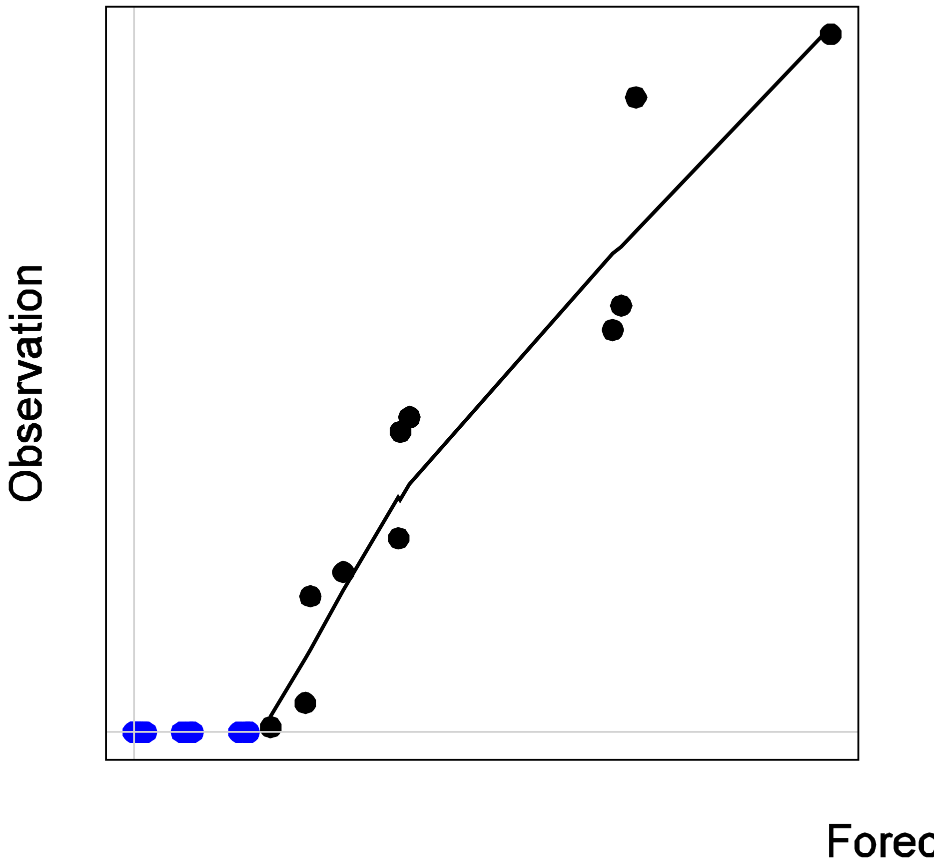
- Statistical methods are applied separately to each *site* and *lead time* (also *variable*)
- But: spatial and temporal dependencies from raw ensembles can be utilized

A. Transformation of ensemble members

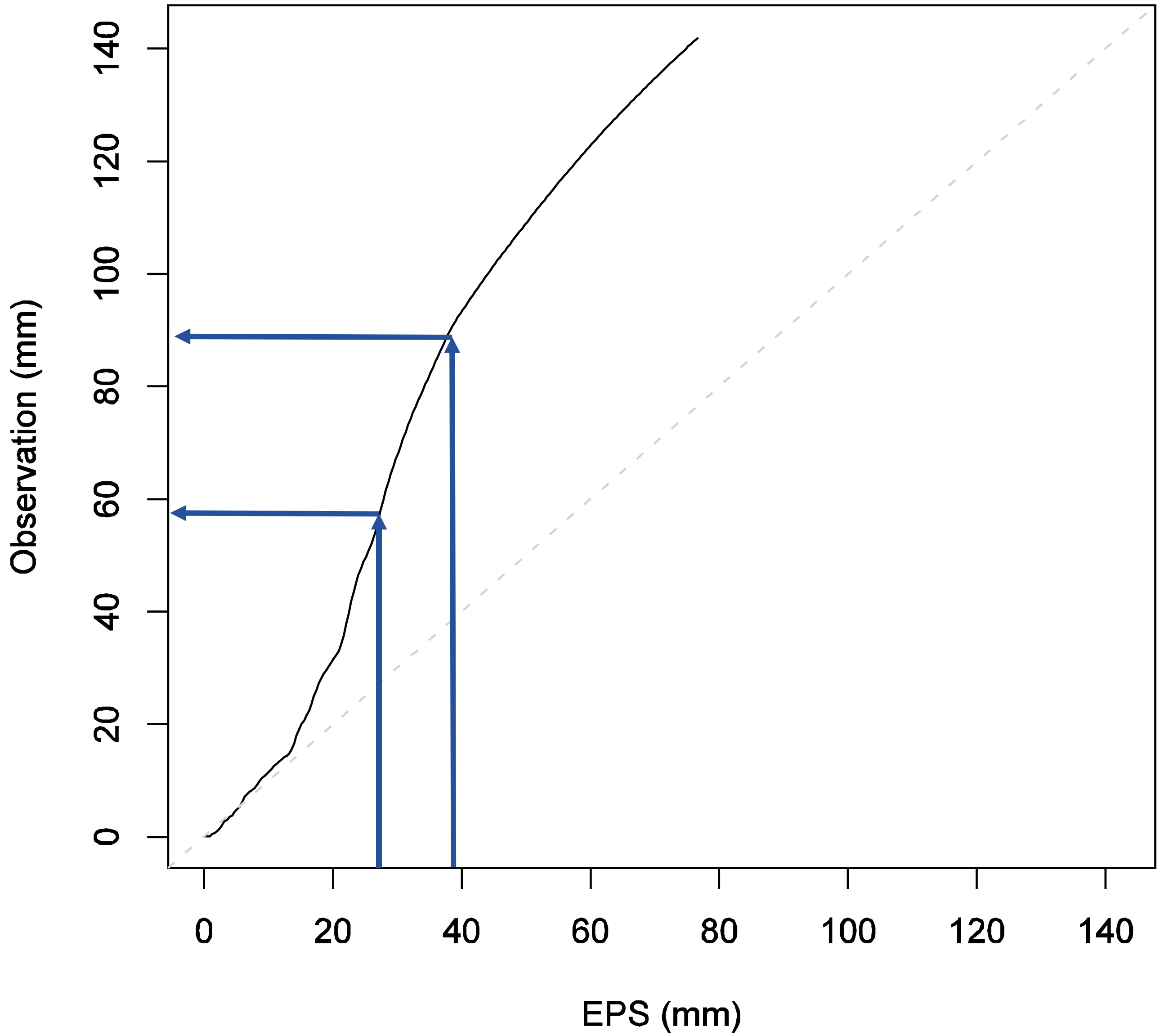
1. Quantile-to-quantile transformation (LQQT)

- Idea
  - Lack of calibration partly due to model biases
  - If model climate equals observed climate …
- Theory
  - If F_{mod} and F_{obs} are CDFs of model and observations, then
  - $Z(x) = F_{obs}^{-1}(F_{mod}(x))$ has distribution F_{obs}
- Practice
  - Sort observations and model data (separately)

LQQT in practice



Lysebotn



Observation (mm)
140
120
100
80
60
40
20
0
0
20
40
60
80
100
120
140
EPS (mm)

1. Quantile-to-quantile transformation with several predictors (REG+LQQT)

- Motivation
  - LQQT applicable only for <u>*one*</u> predictor
  - Other predictors may provide additional information

- Approach
  - Multiple linear regression $\Rightarrow$ predicted precipitation
  - Apply LQQT to the new precipitation predictions

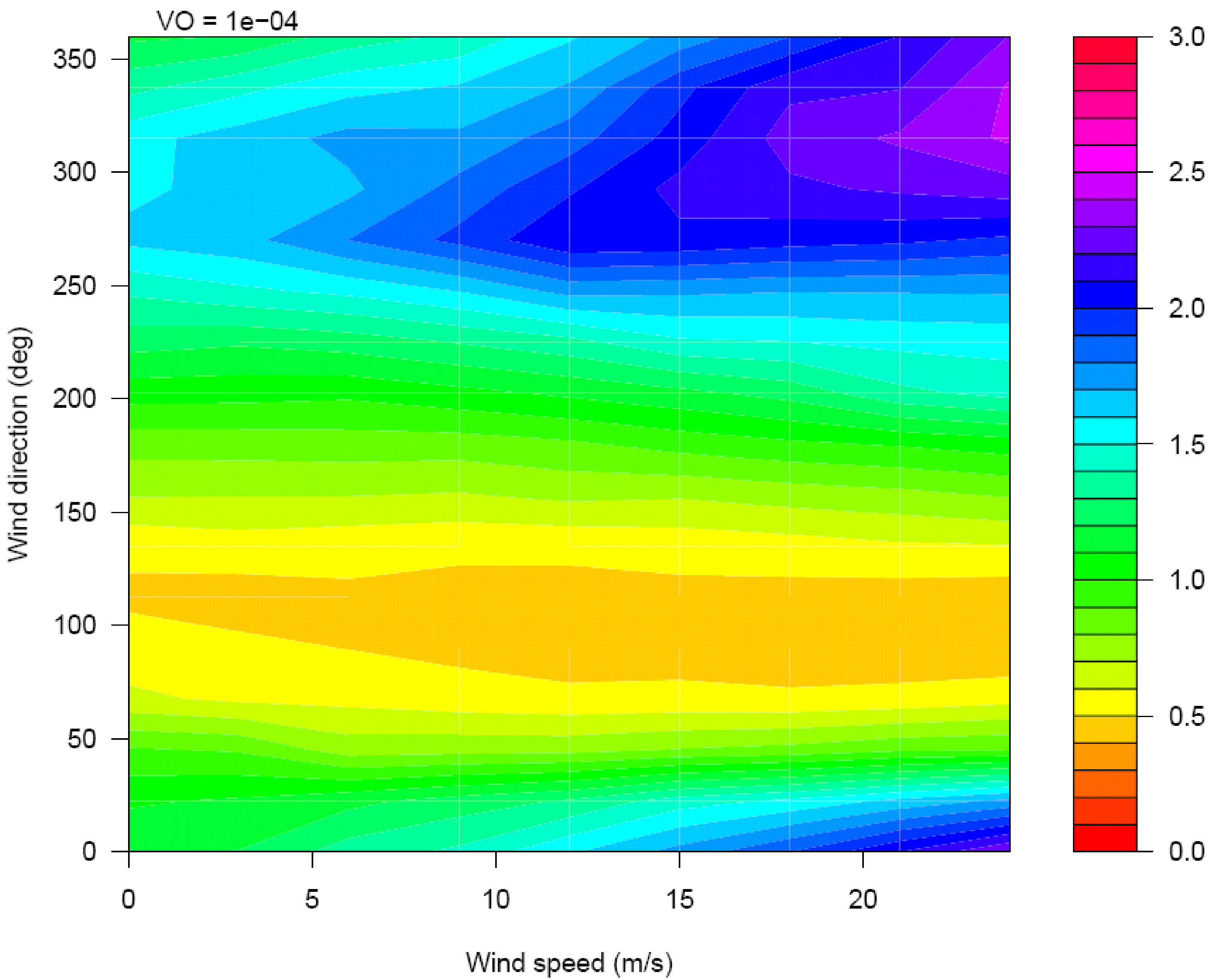
1. Scaling (SCL)

- “Sum observed amounts” / “sum model amounts”

$$s(x) = \frac{\alpha + \sum_t w(x, x_t) R_t^{obs}}{\alpha + \sum_t w(x, x_t) R_t^{\mathrm{mod}}}$$

  - w() = similarity of weather pattern at hand (x) and historical weather pattern (x_t)
  - R^{obs} = observed amounts, R^{mod} = model amounts
  - α = suitable number, such that s(x) $\rightarrow$ 1 for small amounts

Lysebotn


VO = 1e−04
Wind direction (deg)
0
50
100
150
200
250
300
350
Wind speed (m/s)
0
5
10
15
20
0.0
0.5
1.0
1.5
2.0
2.5
3.0

B. Calibration of complete ensemble

Bayesian processor of output/ensemble (BPE)

- Separate statistical models for probability of precipitation and precipitation amounts
- All variables are transformed to standard normal (similar to LQQT)
- Apply Bayes theorem
- Parameter estimation on the transformed data
- Forecast distribution presented on original

Experiments

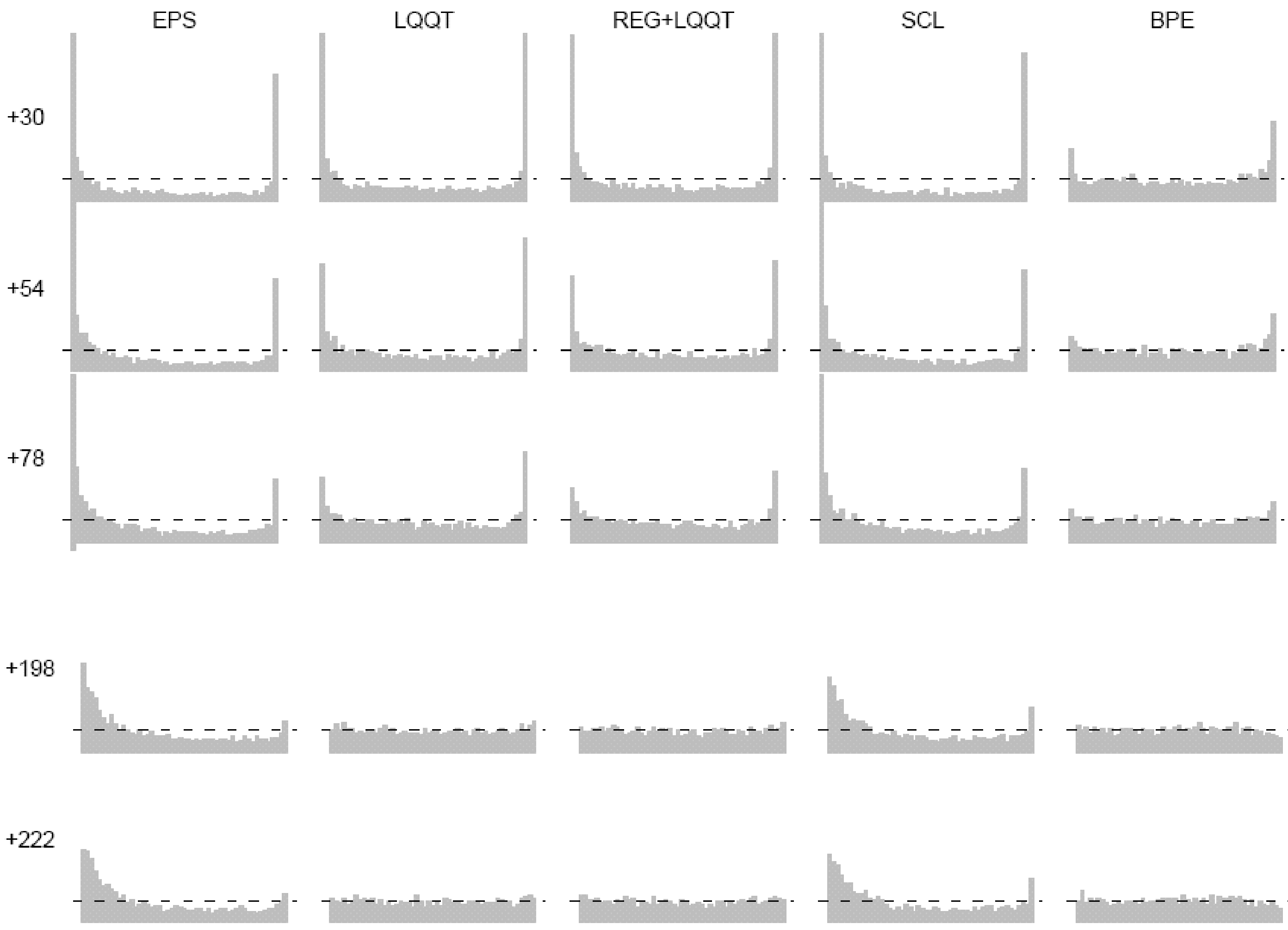
- Observations at 9 locations
  - Lysebotn, Tustervann, Vågslid, Syrstad, Osen, Bygdin, Nelaug, Varaldset og Øyestøl
  - Data from 2004 (training) and 2005 (testing)
- ECMWF EPS prognoser
  - 00 +30, +54, ..., +222 UTC
  - Precipitation, wind speed and direction at 850 hPa, relative vorticity at 850 hPa
  - 50 ensemble members

Validation

- Consider only entire ensemble
  - All methods generate 50 quantiles/members

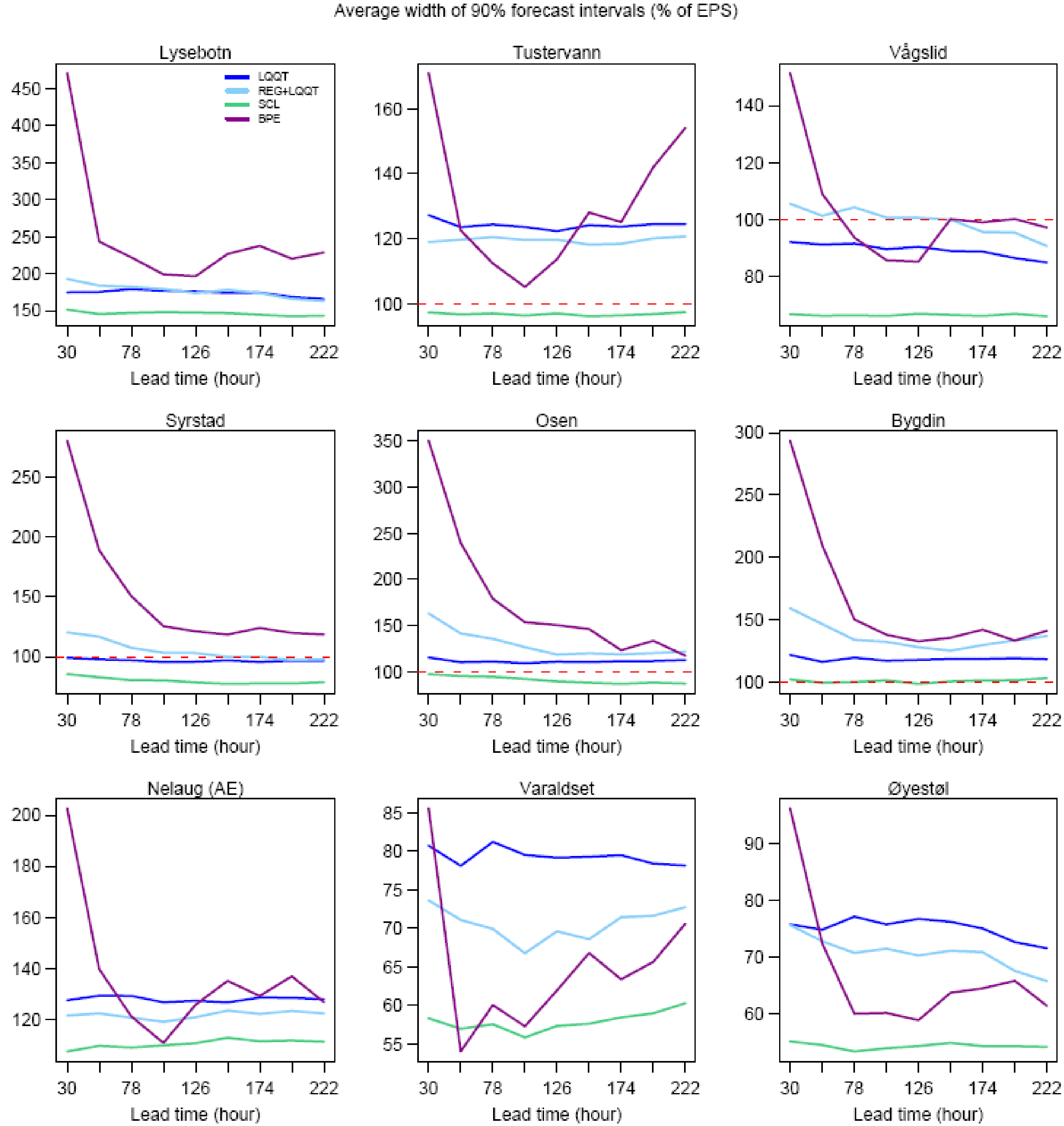
- Validation approach
  - Reliability
    - Verification rank histograms
  - Sharpness
    - Average lengths of 50% and 90% forecast intervals
  - Summary measure
    - Continuous ranked probability score (CRPS)

Verification rank histograms

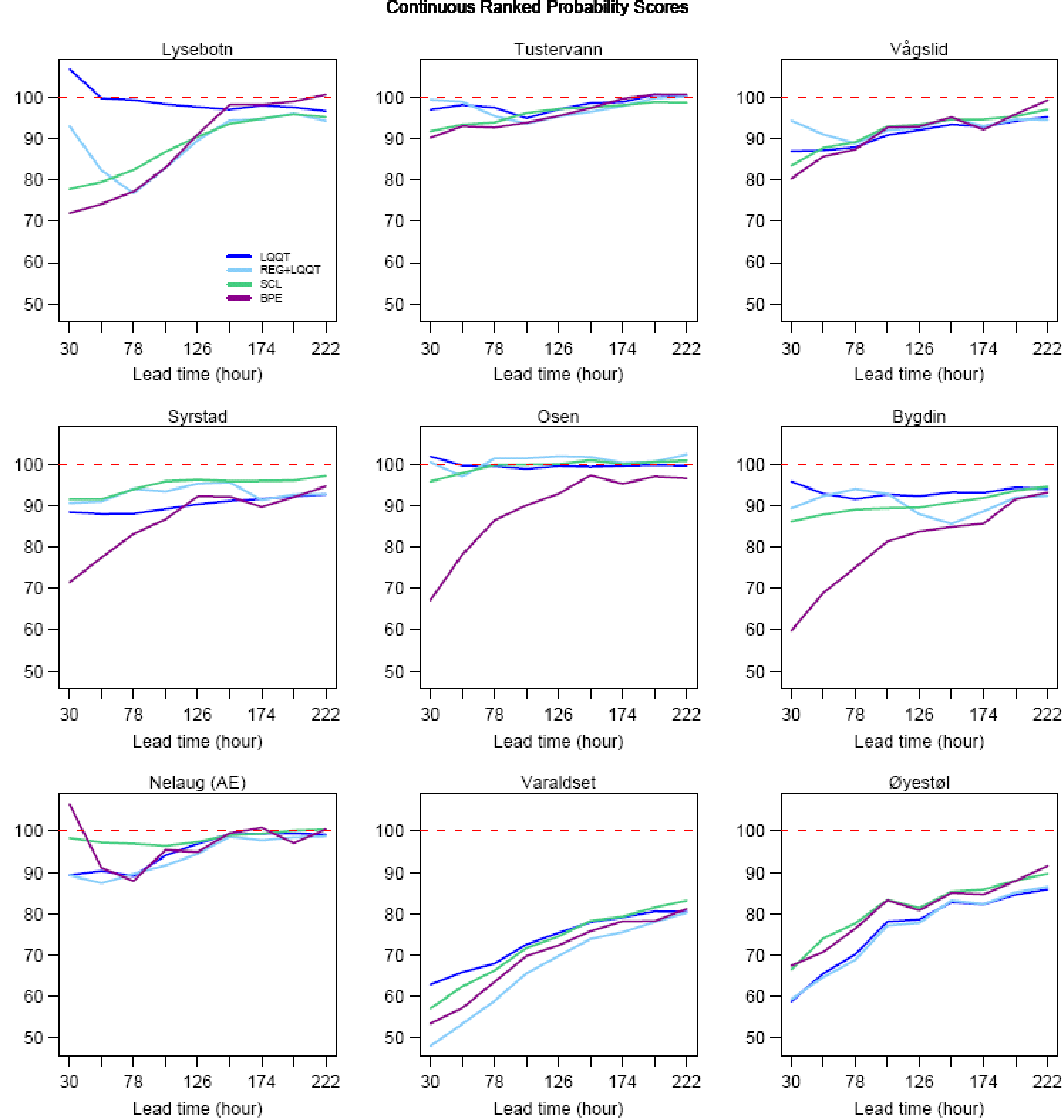


- EPS clearly not well calibrated (too little spread)
- Ensemble member methods (LQQT, REG+LQQT and SCL) not well calibrated, but better than EPS
- BPE quite good, except shortest lead time
- Calibration improves with lead time

Note: some of the EPS bars are clipped (longer than they



- Short intervals best
- BPE intervals quite long for short lead times (to achieve reliability)
- Scaling and raw EPS have the shortest intervals (but not well calibrated)
- At Varaldset og Øyestøl all methods have shorter intervals than raw EPS (and better calibration!)
- Similar results for the 50% intervals



- Low CRPS best (0 optimal)
- CRPS specified in percentage of raw EPS (100%)
- Statistical methods better than raw EPS at most sites and lead times

Concluding remarks

- Statistical methods able to improve ECMWF EPS
  - Large variations across sites
- BPE is best, but
  - Extreme events and estimation of probability of precipitation should be further investigated
  - How to deal with large ensemble still not obvious
- Ensemble member methods
  - Simple to implement
  - Do not provide well-calibrated forecasts

Future

- Further development based on Bayesian Processor of Ensemble
- Calibration of multi-model ensembles
- Quantifying importance of each member/model
  - Do BPE and BMA give similar results?
- Use of reforecasts (ECMWF)
  - Quality as function of length of training period