



Total probabilities of ensemble runoff forecasts

Jon Olav Skøien (1), Konrad Bogner (2), Peter Salamon (1), Paul Smith (3), and Florian Pappenberger (3)

(1) European Commission's Joint Research Centre, IES - CRM, Ispra (VA), Italy (jon.skoien@gmail.com), (2) Swiss Federal Research Institute WSL, Birmensdorf, Switzerland, (3) European Centre for Medium-Range Weather Forecasts, Reading, UK

Ensemble forecasting has a long history from meteorological modelling, as an indication of the uncertainty of the forecasts. However, it is necessary to calibrate and post-process the ensembles as they often exhibit both bias and dispersion errors. Two of the most common methods for this are Bayesian Model Averaging (Raftery et al., 2005) and Ensemble Model Output Statistics (EMOS) (Gneiting et al., 2005). There are also methods for regionalizing these methods (Berrocal et al., 2007) and for incorporating the correlation between lead times (Hemri et al., 2013). Engeland and Steinsland (2014) developed a framework which can estimate post-processing parameters varying in space and time, while giving a spatially and temporally consistent output. However, their method is computationally complex for our larger number of stations, which makes it unsuitable for our purpose.

Our post-processing method of the ensembles is developed in the framework of the European Flood Awareness System (EFAS – <http://www.efas.eu>), where we are making forecasts for whole Europe, and based on observations from around 700 catchments. As the target is flood forecasting, we are also more interested in improving the forecast skill for high-flows rather than in a good prediction of the entire flow regime.

EFAS uses a combination of ensemble forecasts and deterministic forecasts from different meteorological forecasters to force a distributed hydrologic model and to compute runoff ensembles for each river pixel within the model domain. Instead of showing the mean and the variability of each forecast ensemble individually, we will now post-process all model outputs to estimate the total probability, the post-processed mean and uncertainty of all ensembles.

The post-processing parameters are first calibrated for each calibration location, but we are adding a spatial penalty in the calibration process to force a spatial correlation of the parameters. The penalty takes distance, stream-connectivity and size of the catchment areas into account. This can in some cases have a slight negative impact on the calibration error, but avoids large differences between parameters of nearby locations, whether stream connected or not. The spatial calibration also makes it easier to interpolate the post-processing parameters to uncalibrated locations. We also look into different methods for handling the non-normal distributions of runoff data and the effect of different data transformations on forecasts skills in general and for floods in particular.

Berrocal, V. J., Raftery, A. E. and Gneiting, T.: Combining Spatial Statistical and Ensemble Information in Probabilistic Weather Forecasts, *Mon. Weather Rev.*, 135(4), 1386–1402, doi:10.1175/MWR3341.1, 2007.

Engeland, K. and Steinsland, I.: Probabilistic postprocessing models for flow forecasts for a system of catchments and several lead times, *Water Resour. Res.*, 50(1), 182–197, doi:10.1002/2012WR012757, 2014.

Gneiting, T., Raftery, A. E., Westveld, A. H. and Goldman, T.: Calibrated Probabilistic Forecasting Using Ensemble Model Output Statistics and Minimum CRPS Estimation, *Mon. Weather Rev.*, 133(5), 1098–1118, doi:10.1175/MWR2904.1, 2005.

Hemri, S., Fundel, F. and Zappa, M.: Simultaneous calibration of ensemble river flow predictions over an entire range of lead times, *Water Resour. Res.*, 49(10), 6744–6755, doi:10.1002/wrcr.20542, 2013.

Raftery, A. E., Gneiting, T., Balabdaoui, F. and Polakowski, M.: Using Bayesian Model Averaging to Calibrate Forecast Ensembles, *Mon. Weather Rev.*, 133(5), 1155–1174, doi:10.1175/MWR2906.1, 2005.