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Total probabilities of ensemble runoff forecasts

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Ensemble forecasting has for a long time been used as a method in meteorological modelling to indicate the uncertainty of the forecasts. However, as the ensembles often exhibit both bias and dispersion errors, it is necessary to calibrate and post-process them. 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 Engeland and Steinsland (2014) developed a framework which can estimate post-processing parameters which are different in space and time, but still can give a spatially and temporally consistent output. However, their method is computationally complex for our larger number of stations, and cannot directly be regionalized in the way we would like, so we suggest a different path below.

The target of our work is to create a mean forecast with uncertainty bounds for a large number of locations in the framework of the European Flood Awareness System (EFAS – http://www.efas.eu) We are therefore more interested in improving the forecast skill for high-flows rather than the forecast skill of lower runoff levels.

EFAS uses a combination of ensemble forecasts and deterministic forecasts from different 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 find a total probability, the post-processed mean and uncertainty of all ensembles.

The post-processing parameters are first calibrated for each calibration location, but assuring that they have some spatial correlation, by adding a spatial penalty in the calibration process. This can in some cases have a slight negative impact on the calibration error, but 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.

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