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Application of Ensemble Dressing for Hydrological Applications

Durga Lal Shrestha, Thomas Pagano, Qj Wang, and David Robertson
CSIRO Land and Water, Melbourne, Australia

An objective of ensemble forecasting is the adequate characterization of uncertainty. Most operational hydrologic ensemble forecasting systems only account for uncertainty in future climate (e.g. precipitation) forcings, ignoring other sources of uncertainty (e.g. model error). One can derive probabilistic forecasts from the ensemble forecast but the results would be biased, under-dispersive, and unreliable if the ensemble did not account for all sources of uncertainty.

Some methods for quantifying uncertainty involve the attachment of a probability distribution to single-valued forecast (i.e. a control run or an ensemble mean). The limitations of this approach include assumptions about the shape and width of the distribution. Other methods require the production of a set of retrospective ensemble forecasts. In some cases, this can be computationally expensive and can result in very large datasets. Furthermore, many of these studies have been done in weather forecasting contexts; in contrast, hydrologic data is often highly skewed and the errors are autocorrelated and heteroscedastic.

Ensemble dressing is a form of statistical post-processing to include information about the uncertainty of individual ensemble members. First, the historical simulations can be corrected to remove systematic biases. These model residuals come from experiments in which the model is forced with observed historical rainfall and compared to observed streamflow. Next, the simulated and observed flow data are transformed to ensure that model residuals can be fitted to a distribution (e.g. Gaussian). Various transformations were applied, such as Box-Cox and Yeo-Johnson, although the Log(SinH) transform produced the best results in this study. In transformed-space, the error distribution parameters (e.g. mean, standard deviation) are calculated.

Third, an ensemble of streamflow forecasts is generated in realtime. These ensembles may result from forcing the model with a collection of possible future rainfall scenarios. Fourth, the ensemble members are de-biased and transformed using the same method as the first two steps. Fifth, the model error distribution (from step 2) is attached to each ensemble member from the previous step. The individual probability density functions for each ensemble are summed and normalized into a final forecast probability density function. Finally, the results are untransformed and the probabilistic forecast generated.

This method has been applied to a series of Southeast Australian catchments, using fully retrospective ensemble forecasts of monthly and daily streamflow. The ensemble dressed forecasts are verified with various ensemble verification metrics, such as the continuous ranked probability score, rank histograms and attributes diagrams. The results demonstrate that ensemble dressed forecasts are more skillful and reliable than the undressed ensembles.

This technique fills a gap by proposing an ensemble post-processing technique that considers multiple sources of uncertainty while requiring only minimal computational resources. As such, this method would be well suited for operational forecasting applications.