



## On the proper use of Ensembles for Predictive Uncertainty assessment

Ezio Todini (1), Gabriele Coccia (2), and Enrique Ortiz (3)

(1) BiGeA — University of Bologna, Bologna, Italy (ezio.todini@unibo.it), (2) Princeton University, Princeton, NJ (USA) (gcoccia@princeton.edu), (3) Idrologia e Ambiente Srl, Napoli, Italy (enrique.ortiz@idrologiaeambiente.it)

Probabilistic forecasting has become popular in the last decades. Hydrological probabilistic forecasts have been based either on uncertainty processors (Krzysztofowicz, 1999; Todini, 2004; Todini, 2008) or on ensembles, following meteorological traditional approaches and the establishment of the HEPEX program (<http://hepex.irstea.fr>). Unfortunately, the direct use of ensembles as a measure of the predictive density is an incorrect practice, because the ensemble measures the spread of the forecast instead of, following the definition of predictive uncertainty, the conditional probability of the future outcome conditional on the forecast.

Only few correct approaches are reported in the literature, which correctly use the ensemble to estimate an expected conditional predictive density (Reggiani et al., 2009), similarly to what is done when several predictive models are available as in the BMA (Raftery et al., 2005) or MCP (Todini, 2008; Coccia and Todini, 2011) approaches.

A major problem, limiting the correct use of ensembles, is in fact the difficulty of defining the time dependence of the ensemble members, due to the lack of a consistent ranking: in other words, when dealing with multiple models, the *i*th model remains the *i*th model regardless to the time of forecast, while this does not happen when dealing with ensemble members, since there is no definition for the *i*th member of an ensemble.

Nonetheless, the MCP approach (Todini, 2008; Coccia and Todini, 2011), essentially based on a multiple regression in the Normal space, can be easily extended to use ensembles to represent the local (in time) smaller or larger conditional predictive uncertainty, as a function of the ensemble spread. This is done by modifying the classical linear regression equations, implying perfectly observed predictors, to alternative regression equations similar to the Kalman filter ones, allowing for uncertain predictors. In this way, each prediction in time accounts for both the predictive uncertainty of the ensemble mean and that of the ensemble spread.

The results of this new approach are illustrated by using data and forecasts from an operational real time flood forecasting.

Coccia, G. and Todini, E. 2011. Recent developments in predictive uncertainty assessment based on the Model Conditional Processor approach. *Hydrology and Earth System Sciences*, 15, 3253-3274. doi:10.5194/hess-15-3253-2011.

Krzysztofowicz, R. 1999 Bayesian theory of probabilistic forecasting via deterministic hydrologic model, *Water Resour. Res.*, 35, 2739–2750.

Raftery, A. E., T. Gneiting, F. Balabdaoui, and M. Polakowski, 2005. Using Bayesian model averaging to calibrate forecast ensembles, *Mon. Weather Rev.*, 133, 1155-1174.

Reggiani, P., Renner, M., Weerts, A., and van Gelder, P., 2009. Uncertainty assessment via Bayesian revision of ensemble streamflow predictions in the operational river Rhine forecasting system, *Water Resour. Res.*, 45, W02428, doi:10.1029/2007WR006758.

Todini E. 2004. Role and treatment of uncertainty in real-time flood forecasting. *Hydrological Processes* 18(14), 2743\_2746

Todini, E. 2008. A model conditional processor to assess predictive uncertainty in flood forecasting. *Intl. J. River Basin Management*, 6(2): 123-137.