Journal of Hydrology 551 (2017) 555–576

Contents lists available at ScienceDirect

Journal of Hydrology

journal homepage: www.elsevier.com/locate/jhydrol

Research papers

The multi temporal/multi-model approach to predictive uncertainty assessment in real-time flood forecasting

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ARTICLE INFO

Article history:
Received 17 February 2017
Received in revised form 14 June 2017
Accepted 15 June 2017
Available online 19 June 2017
This manuscript was handled by Corrado Corradini, Editor-in-Chief, with the assistance of Subashisa Dutta, Associate Editor

Keywords:
Predictive uncertainty
Multi-model and multi-temporal approach
Flooding probability
Hydrometric thresholds
Early-warning

ABSTRACT

This work extends the multi-temporal approach of the Model Conditional Processor (MCP-MT) to the multi-model case and to the four Truncated Normal Distributions (TNDs) approach, demonstrating the improvement on the single-temporal one. The study is framed in the context of probabilistic Bayesian decision-making that is appropriate to take rational decisions on uncertain future outcomes. As opposed to the direct use of deterministic forecasts, the probabilistic forecast identifies a predictive probability density function that represents a fundamental knowledge on future occurrences. The added value of MCP-MT is the identification of the probability that a critical situation will happen within the forecast lead-time and when, more likely, it will occur.

MCP-MT is thoroughly tested for both single-model and multi-model configurations at a gauged site on the Tiber River, central Italy. The stages forecasted by two operative deterministic models, STAFOM-RCM and MISDc, are considered for the study. The dataset used for the analysis consists of hourly data from 34 flood events selected on a time series of six years.

MCP-MT improves over the original models' forecasts: the peak overestimation and the rising limb delayed forecast, characterizing MISDc and STAFOM-RCM respectively, are significantly mitigated, with a reduced mean error on peak stage from 45 to 5 cm and an increased coefficient of persistence from 0.53 up to 0.75.

The results show that MCP-MT outperforms the single-temporal approach and is potentially useful for supporting decision-making because the exceedance probability of hydrometric thresholds within a forecast horizon and the most probable flooding time can be estimated.

1. Introduction

The severe effects of flood events are mitigated through structural measures often used along with complementary non-structural measures, such as Flood Forecasting and Warning Systems (FFWSs) able to provide monetary benefits and improvement of the population resilience (Pappenberger et al., 2015).

Real-time flood forecasting modelling is an essential component of FFWSs, providing important information on the future evolution of floods, i.e. stage and/or discharge forecasts useful for addressing decision-making for flood risk mitigation. The predictions of all flood forecasting models are affected by many errors thus leaving the decision-maker with residual uncertainty on future events (Todini, 2004; Montanari and Koutsoyiannis, 2012). Many contributions on the assessment of the uncertainty of hydrological predictions have been made available in the scientific literature, often focused on the identification of the different sources of uncertainty (Krzysztofowicz, 2002; Montanari and Brath, 2004; Clark and Slater, 2006; Vrugt and Robinson, 2007; Ebtehaj et al., 2010; He et al., 2011; Legleiter et al., 2011; Sikorska et al., 2012, just to cite a few). Moreover, the ensemble prediction approach has been investigated and applied in hydrology (Thielen et al., 2008; Cloke and Pappenberger, 2009; Addor et al., 2011; Regonda, 2013) by taking advantage from the fast available computing resources to generate many ensembles as an alternative to the full probability density function. Ensemble approaches were in particular advocated by the Hydrologic Ensemble Prediction EXperiment (HEPEX, www.hepex.org) addressed to develop useful hydrologic ensemble forecast procedures within global and multidisciplinary collaborations. Also, multivariate post-processing methods have been applied to deterministic or

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http://dx.doi.org/10.1016/j.jhydrol.2017.06.030
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ensemble predictions, such as the Schaake Shuffle or ensemble copula coupling (Schaake et al., 2007; Schefzik et al., 2013).

Many studies are now available on assessing probabilistic forecasting starting from deterministic forecast by modelling the uncertainty in single-valued hydrologic forecasts, also dealing with single-valued forecasts developed for multiple lead-times (Montanari and Grossi, 2008; Smith et al., 2012; Hoss and Fischbeck, 2015). However, the introduction of the Hydrological Uncertainty Processor (Krzysztofowicz, 1999; Krzysztofowicz and Kelly, 2000) represented a milestone in the estimation of flood predictive uncertainty (PU) defined as the probability density of a future outcome conditional on all the available information, usually provided by model forecasts (Krzysztofowicz, 1999; Todini, 2008; Coccia and Todini, 2011). In the Bayesian decision approach, PU estimate provides the best knowledge on a future outcome and is a fundamental tool for reaching appropriate informed decisions.

Various processors for PU estimate have been proposed starting from Krzysztofowicz (1999) who laid the basis for PU estimation by introducing the Bayesian Forecasting System (BFS) based on a set of historical recorded data and one model forecast (Krzysztofowicz and Kelly, 2000). Among several other approaches for PU assessment, the Bayesian Model Averaging (Raftery, 1993; Raftery et al., 2005; Vrugt and Robinson, 2007), an approximation of the predictive conditional density, can be mentioned. It aims at assessing the mean and variance of any future value of the predictand conditional upon several model forecasts.

If not appropriately treated, these techniques imply homoscedasticity of the error, which is assumed independent from the magnitude of the observed or forecasted values. In real cases, this assumption leads to a lack of reliability, especially in reproducing high flows. Recently, to overcome this problem the Quantile Regression (Koenker, 2005) approach was used (Weerts et al., 2011), which tries to represent the error heteroscedasticity identifying a linear variation of the quantiles of the PU as a function of the model forecast magnitude. Multiple Linear Regression approaches, such as the Model Output Statistics (MOS) (Glahn and Lowry, 1972; Wilks, 1995) or the EMOS (Ensemble Model Output Statistics) (Gneiting et al., 2005), were also used in the past as uncertainty post processors in meteorological applications. Some works also treated the heteroscedasticity by direct transformations, such as the Box-Cox (Box and Cox, 1964; Franchini et al., 2011). Moreover, the time dependencies of variance were applied to seasonal models or long term forecasting models (Wang et al., 2005) and other state-dependent parameterizations of variance (Engle, 1982) were also used in hydrological applications along with data-driven models (Romanowicz et al., 2006) or Kalman filter approaches (Young et al., 2014).

Following the same ideas of converting both observations and model(s) predictions into the Normal space as in Krzysztofowicz (1999), Todini (2008) proposed the Model Conditional Processor (MCP) for directly estimating the predictive density in a more general way, which also allowed for multi-model approaches. More recently, Zhao et al. (2011) in the General Linear Model Post-Processor (GLMPP) as well as Wang and Robertson (2011) in their approach to seasonal flows forecasting used probabilistic processors based on equations quite similar to MCP. Moreover, MCP was extended to the multi-model approach by Coccia and Todini (2011), allowing for a simple predictive density, to be used in decision, although based on ‘multiple forecasts’ using different predictive models at the same time. Afterwards, to show the strong links between MCP and the Bayesian Forecasting System (BFS) by Krzysztofowicz (1999), Todini (2013) also proved that the two approaches coincide at lag-one forecasts, while MCP outperforms BFS when extending the forecasts to longer lead-times. The usefulness of the MCP has been demonstrated also in other research areas such as hydrodynamic studies (e.g. Camacho et al., 2015).

Moreover, the MCP was made able to use two joint Truncated Normal Distributions (TNDs) to improve adaptation to low and high flows. As pointed out by a number of authors (Weerts et al., 2011; Coccia and Todini, 2011), the assumption of the joint distribution should take into account errors heteroscedasticity. Weerts et al. (2011) proposed the Quantile Regression methodology, but this technique has a few disadvantages. Specifically, the use of the Quantile Regression requires a high number of parameters and, hence, there is a high risk to overfit the calibration data with a consequent loss of generalization ability. Therefore, Coccia and Todini (2011) proposed to use the Truncated Normal Distributions (TNDs) in order to differentiate the uncertainty associated to high flows and low flows.

However, although the basic approach presented by Coccia and Todini (2011) answers to questions such as ‘*What is the probability that the real water level will be higher than a threshold at 24th hour from now*?’ decision-makers are more eager to provide an answer to other questions such as ‘*What is the probability the threshold will be exceeded within the next 24 h?*‘ and ‘*At what time the threshold will be more likely exceeded within the next 24 h?’*. The multi-model approach cannot provide answers to these new questions and a multi-temporal approach must be considered. Assessing the probability of at least one threshold exceedance “within” a given time horizon, requires in fact the development of the joint predictive probability density for all the intervals within the time horizon. To understand why let us use its analogy with the well known derivation of the probability of at least one exceedance of the T years return period flood within the N years of lifetime of a dyke or a dam. The solution to both problems is defined as 1 minus the probability of non exceedance, which can be estimated via the joint probability function. In the extreme values case the joint can be easily assessed since the yearly maxima occurrences can be reasonably assumed independent and the joint results from the product of the marginal distributions. This independence assumption cannot be made in the case of short term forecasting where the occurrences are definitely not independent and a proper joint predictive density assessment is needed. This is why it is not possible to assess the probability of overtopping “within a specified time interval” using a single fixed time forecast. The forecast could be certainly repeated for all the different lead-times in the specified time interval, but in this way the information on the high dependence of errors from one interval to the next would be lost. On the contrary, this dependence is captured by the joint probability distribution.

We would also like to stress the advantage for using the proposed MCP-MT approach in the Normal space in order to assess the joint predictive probability. On the one hand the extension of single and multi-model MCP to the multi-temporal is straightforward and computationally efficient, and, on the other hand because the assessment of the joint distribution via an ensemble approach would require the generation of an extremely large number of ensemble members.

The multi-temporal approach was originally introduced by Krzysztofowicz (2008) for the BFS, but it was rather complex requiring large computational efforts. Following the same idea, Coccia (2011) implemented Krzysztofowicz (2008) concepts as a straightforward modification of the multi-model MCP developed by Coccia and Todini (2011). Recently, a preliminary application has been performed for a case study in India for the single-model configuration (Barbetta et al., 2016).

The multi-temporal approach of MCP is here extended to the multi-model case and to the 4 TNDs approach for the division of the data in order to represent the low flows, the rising limbs, the peak flows and the recession limbs. The processor is thoroughly investigated to provide appropriate answers to the above mentioned specific questions also demonstrating the benefits