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# Identification of the best multi-model combination for simulating river discharge

Arun Kumar *, R. Singh, Prachi Pratyasha Jena, Chandranath Chatterjee, Ashok Mishra

*Indian Institute of Technology Kharagpur, Agricultural & Food Engineering Department, Kharagpur 721 302, India*

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SUMMARY

This paper focuses on the selection of the best multi-model ensemble method that is subsequently used to create an ensemble for the discharge estimation in a catchment of the Mahanadi river basin in India. Ten different multi-model ensemble methods, viz., mean, median, trimmed mean, unconstrained and constrained multiple linear regression, weighted mean based on calibration performance (two variants), linear programming, simple model average and multi model super ensemble, are compared using calibrated and validated data of eight popular hydrological models, MIKE SHE, SWAT, HEC-HMS, AWBM, SIMHYD, SACRAMENTO, SMAR and TANK. Constrained multiple linear regression (MLR_C) method is found to be the most suitable multi-model ensemble method for the study area. MLR_C method is subsequently used to develop 189 possible multi-model ensembles. These ensembles are evaluated for categorical and temporal accuracy, using a proposed *SCORE* that includes normalized relative operating characteristic (ROC) area and normalized number of skillful days. The results show that an ensemble having five models, one physically based (SWAT) and four conceptual (AWBM, SIMHYD, SACRAMENTO and SMAR), performs the best for the chosen catchment. The best performing ensemble also outperforms all eight individual models in simulating the observed discharge and flow volume. Furthermore, uncertainty in simulating river discharge due to all sources collectively is analyzed through uncertainty analysis.



## 1. Introduction

Watershed models have become an essential tool in addressing a wide spectrum of problems in water resources sector, including planning, development, design, operation, and management. With advancement of modeling technology, several hydrological models, ranging from lumped conceptual to physically-based distributed models, have been developed with regards to data requirement and process parameterization (Singh and Woolhiser, 2002). However, application of these models brings several kinds of uncertainty, dealing with the model structure, model parameters and input data (Beven and Freer, 2001). Conventionally, these uncertainties are handled through model calibration and data assimilation (Liu and Gupta, 2007; Moradkhani et al., 2005a,b; Vrugt et al., 2005). Probabilistic approaches such as generalized likelihood uncertainty estimation (GLUE) method, a version of Monte Carlo simulation, have also been proposed to handle the uncertainty in model parameters (Beven and Binley, 1992; Beven and Freer, 2001). In few studies, the approaches based on Bayesian model averaging (BMA) method have also been applied successfully (Ajami et al., 2007). A few studies have addressed the uncertainty issue through ensemble modeling (Georgakakos and Krzysztofowicz, 2001; Viney et al., 2009; Schellekens et al., 2011), and ensemble systems have been used to account for uncertainty in input data, model parameter and model structure individually or combined uncertainty due to these (Gourley and Vieux, 2005, 2006). However, in order to provide full range of uncertainty, ensemble must include variety of ensemble members (Cloke and Pappenberger, 2009).

Ensemble prediction methods were developed to overcome the limitations of deterministic weather forecasting (Parker, 2010) in relation to uncertainty and chaos (Ehrendorfer, 1997), and have played pivotal role in simulation based weather and climate predictions. Though ensemble hydrological modeling started way back in 1970s (Twedt et al., 1977), it gathered momentum only in the last decade or so, especially through the cooperative initiatives such as Distributed Model Inter Comparison Project (DMIP) (Smith et al., 2004) and Hydrologic Ensemble Prediction EXperiment (HEPEX) project (Schaake et al., 2007).

Ensemble modeling can be widely applied in different sectors of water resources modeling with the concept of ensemble used for reducing errors with an optimal bias and variance trade-off (Baker and Ellison, 2008). It encompasses a large number of

* Corresponding author. Tel.: +91 9434201607; fax: +91 3222 282244.
*E-mail address:* arun.kgpiit@gmail.com (A. Kumar).

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approaches to combine different model predictions that lead to a single prediction. Single model ensemble involves use of different realizations of a single deterministic model or models of same type, whereas multi-model ensemble involves realizations from different models of varying structural complexity (Baker and Ellison, 2008; Viney et al., 2009). Multi-model ensembles, however, outperform individual models, and tend to perform better than single-model ensembles in weather prediction and streamflow simulation (Doblas-Reyes et al., 2005; Georgakakos et al., 2004; Ziehmann, 2000).

Several methods of combining outputs of different models like simple model average (SMA), the weighted average method (WAM), constrained multiple linear regression (MLR_C), and multi model super ensemble (MMSE) (Krishnamurti et al., 2000) have been used in previous studies (Dickinson, 1975; Makridakis and Winkler, 1983; Shamseldin et al., 1997; Abrahart and See, 2002; Oudin et al., 2006; Fenicia et al., 2007). A major challenge in ensemble modeling, however, is to determine the ensemble size and to identify the right constituent models. This is because the 'best' individual model may not necessarily be a good choice in modeling practice (Perrone and Cooper, 1993); and the best ensembles may not necessarily contain the best individual models (Viney et al., 2009).

The present study focuses on determining the best model combination and ensemble size with regards to the best simulation performance. We have pooled the simulation results of eight popular hydrological models, viz., MIKE SHE, SWAT, HEC-HMS, AWBM, SIMHYD, SACRAMENTO, SMAR and TANK (Singh and Woolhiser, 2002), using ten multi-model ensemble methods to identify the most suitable method for the study area. Root mean square error (RMSE) and Pearson's correlation coefficient ($R$) have been used to evaluate the performance of the ensemble methods (Georgakakos et al., 2004). Subsequently, the best method is applied for developing 189 different ensembles. A framework that includes two indices, viz., ROC (relative operating characteristic) curve area and 'number of skillful days', ($N_d$), has been developed for identifying the best performing ensemble. Subsequently, quantile regression technique (Dogulu et al., 2014; Koenker and Bassett, 1978; Solomatine and Shrestha, 2009; Weerts et al., 2011) has been used to carry out the uncertainty analysis for the chosen ensemble to ascertain the hydrological uncertainty from all sources collectively.

This paper is organized as follows: in Section 2, we present the brief introduction of study area, data used and the methodology of combining various models, including the details of the evaluation technique. In Section 3 results are presented. This is followed by discussion (Section 4) and conclusions (Section 5).

## 2. Study area and data

Kesinga catchment of Mahanadi River Basin, located in Odisha, India (Fig. 1) is chosen as the study area. The catchment lies between 19°16′10″ and 20°44′42″N latitudes, and 82°02′50″ and 83°24′09″E longitudes, and covers an area of 12,371 km$^2$. Boundary and topography map of the catchment is derived from Shuttle RADAR Topography Mission (SRTM) image of 90 m resolution which is downloaded from Consultative Group on International Agricultural Research-Consortium for Spatial Information (CGIAR-CSI) website. Land use/land cover map is derived from LANDSAT -7 (ETM+) images which are downloaded from Global Land Cover Facility (GLCF) website. Soil map is collected from the National Bureau of Soil Survey and Land Use Planning (NBSS & LUP), Kolkata and corresponding soil properties are estimated using Rosetta 1.0 (Schaap et al., 2001). Daily rainfall and temperature data of seven meteorological stations are collected from India Meteorological Department (IMD), Bhubaneswar for the period 2004–2009. Thiessen polygon method is used to obtain the average daily rainfall of the catchment from raingauge stations data. The pre- and post-monsoon groundwater table depths at 32 different locations in the catchment are collected from hydrometry, Bhubaneswar. Reference evapotranspiration is determined by the Hargreaves equation using DSS_ET software (Bandyopadhyay et al., 2012). The discharge data at the outlet of the catchment is obtained from Central Water Commission (CWC), Bhubaneswar for the period June 2004–May 2009. The data is split in two parts: June 2004–May 2007, which is used for calibration, and June 2007–May 2009, which is used

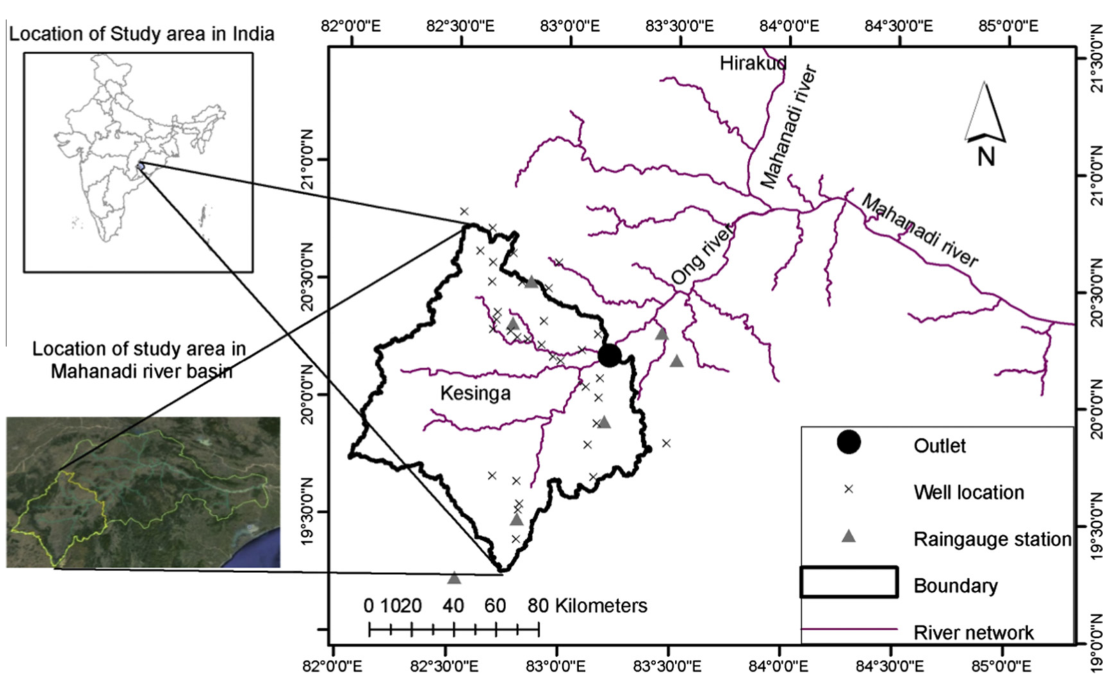


**Fig. 1.** Index map of Kesinga catchment in Mahanadi river basin, India.