Hydrol. Earth Syst. Sci. Discuss., 10, 675–697, 2013
www.hydrol-earth-syst-sci-discuss.net/10/675/2013/
doi:10.5194/hessd-10-675-2013

Hydrology and Earth System Sciences Discussions

Fuzzy committees of specialised rainfall-runoff models: further enhancements

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Received: 29 November 2012 – Accepted: 3 December 2012 – Published: 15 January 2013

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Published by Copernicus Publications on behalf of the European Geosciences Union.

Abstract

Often a single hydrological model cannot capture the details of a complex rainfall-runoff relationship, and a possibility here is building specialised models to be responsible for a particular aspect of this relationship and combining them forming a committee model. This study extends earlier work of using fuzzy committees to combine hydrological models calibrated for different hydrological regimes – by considering the suitability of the different weighting function for objective functions and different class of membership functions used to combine the local models and compare them with global optimal models.

1 Introduction

Conceptual hydrological models are based on fluxes and storages representing relevant hydrological processes and one of the challenges is to identify a set of parameters characterizing the behaviour of time-varying stream flows in a catchment. In lumped models the parameters cannot be measured directly due to the dimensional and scaling problems (Beven, 2000). These are computed based on the measurement of meteorological forcing data to produce model predictions that are as close as possible to the observed discharge data using some degree of expertise and experience. Typically this approach focuses on the single model using the best single set of parameters. However the model produced by one best set of parameters might not equally well describe the characteristic of the hydrological processes for all ranges of flow, and multiple models can be built from different components of flow hydrograph that correspond to characteristic of different flow regimes. These models can be then combined providing a more comprehensive and accurate representation of catchment processes. Such models are referred to as multi-models, or committee models.

The idea of multi-model approach is not new in hydrological modelling – for example early works of Keefer and McQuivey (1974), Todini and Wallis (1977), Bruen (1985)

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and Becker and Kundzewicz (1987) who were building piece-wise linear models instead of the overall linear hydrological model. Cavadias and Morin (1986) aggregated several watershed models which were considered by WMO (1986) for intercomparison of their model performances. Juemoe et al. (1987) combined a conceptual model and a statistical model which is known as synthesized constrained linear systems model. This model was developed by combination of Xinanjiang model (Zhao, 1977) and constrained linear system model (Todini and Wallis, 1977). McLeod et al. (1987) combined three models namely, transfer function noise model, periodic autoregressive model and conceptual model for flow forecast. Since then various authors were exploring various approaches to identification of different hydrological regimes and the ways of combining specialised models, both process-based and data driven, e.g. Shamseldin et al. (1997); Abrahart and See (2002); Solomatine and Xue (2004); Anctil and Tape (2004); Solomatine (2006); Oudin et al. (2006); Ajami et al. (2006); Fenicia et al. (2007); Nasr and Bruen (2008); Cullmann et al. (2008) and Toth (2009).

This paper continues to explore and improve the dynamic combination "fuzzy committee" method outlined in Solomatine (2006) and further developed and tested in Fenicia et al. (2007). Weights assigned to each specialised model's output are based on optimally designed fuzzy membership functions, and they may be different at every time step depending on the current value of flow. In the present paper we test the performance of several weighting schemes used in calculating objective functions, different membership functions used to combine models, and we are doing this employing validation of all built models. Two more case studies are considered. Two approaches of optimization are used (i) multi objective optimization Non-dominated Sorted Genetic Algorithms (NSGA II) by Deb et al. (2002) to find Pareto optimal solutions of local models, (ii) Single objective optimization – Genetic Algorithm (GA) by Goldberg (1989) and Adaptive Cluster Covering Algorithm (ACCO) by Solomatine (1999) are used to calibrate optimal local and single global models.

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2 Methodology

2.1 Lumped conceptual modelling

A simplified version of HBV model (Lindstörm et al., 1997; Fenicia et al., 2007) is used for study. This is a lumped conceptual hydrological model which includes conceptual numerical descriptions of the hydrological processes at catchment scale. The model comprises subroutines for snow accumulation and melt, soil moisture accounting procedure, routines for runoff generation, and a simple routing procedure. The model has 13 parameters, however only 9 parameters are effectively used when there is no snowfall.

2.2 Building specialised models

We build several sub-models can be built instead of using only one model to better characterize the various sub-processes determining the catchment hydrological behaviour. The details of such an approach have been reported in Fenicia et al. (2007), and it is briefly outlined below, complemented by the possibilities of its further improvement. We considered high flows and low flows as distinctive regimes, or states of the system behaviour. Our aim was to accurately reproduce the system response during both regimes. In order to evaluate the performance of the single hydrological model in both conditions, the two weighted objective functions are used, where one is stressing the model error with respect to low flow simulation, and the other stressing the model error with respect to high flows.

The two objective functions are defined as follows:

$$\mathrm{RMSE}_{\mathrm{LF}} = \sqrt{\frac{1}{n}\left(\sum_{i=1}^{n}(Q_{\mathrm{s},i} - Q_{\mathrm{o},i})^2 \cdot W_{\mathrm{LF},i}\right)} \quad (1)$$

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$$\mathrm{RMSE}_{\mathrm{HF}} = \sqrt{\frac{1}{n}\left(\sum_{i=1}^{n}(Q_{\mathrm{s},i} - Q_{\mathrm{o},i})^2 \cdot W_{\mathrm{HF},i}\right)} \tag{2}$$

$$W_{\mathrm{LF},i} = (l)^N \tag{3}$$

$$W_{\mathrm{LF},i} = \begin{cases} 0, & \text{if } l > \alpha \\ (1 - l*(1/2 - \alpha))^N, & \text{if } l \le \alpha \end{cases} \tag{4}$$

$$W_{\mathrm{HF},i} = (h)^N \tag{5}$$

$$W_{\mathrm{HF},i} = \begin{cases} 1, & \text{if } h > \alpha \\ (h/\alpha)^N, & \text{if } h \le \alpha \end{cases} \tag{6}$$

$$l = \frac{Q_{\mathrm{o,max}} - Q_{\mathrm{o},i}}{Q_{\mathrm{o,max}}}, \quad h = \frac{Q_{\mathrm{o},i}}{Q_{\mathrm{o,max}}}; \tag{7}$$

where n: total number of time steps; $Q_{\mathrm{s},i}$: simulated flow for the time step i; $Q_{\mathrm{o},i}$: observed flow for the time step i; $Q_{\mathrm{o,max}}$: maximum observed flow, N: power value for quadratic function = 2 and cubic function = 3, and α: threshold for selecting weights of flows. The two weighting functions W_{LF} and W_{HF} allow placing a stronger weight on the low or on the high portions of the hydrograph. As a result, $\mathrm{RMSE}_{\mathrm{LF}}$ places a stronger weight on low flows errors and a weaker weight on high flows errors than $\mathrm{RMSE}_{\mathrm{HF}}$. By computing both objective functions over the whole range of discharges, both functions constrain the model to fit the entire hydrograph.

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2.3 Combining specialised models

The specialised models are built under the conditions of different regimes of catchment hydrological responses and are combined using appropriate combining scheme. However the issue is how to handle the compatibility at the boundaries between the two different specialised models. One of the possible ways is to use a soft weighting scheme that switches smooth transition between boundaries. The contribution of each specialised model makes use of a fuzzy attribution of weights so-called "fuzzy committee" described by Solomatine (2006). In this weighting scheme first assigned two transitional parameters (γ, δ) and the values of membership functions corresponding to each specialised model. The membership function of low flow model assigned 1 when the simulated flow is below the parameter γ, then starting to decrease in the proximity of the region boundary when flow between γ and δ; and decreasing to zero beyond the boundary when the flow is above δ (see Fig. 2). Similarly the membership function of the high flow model follows as viva versa of low flow model. These membership functions for the two local models are described in Eqs. (9) and (10). The outputs of models are multiplied by the weights that depend on the value of flow and then normalised which is given in Eq. (8).

The committee model defines as follow:

$$Q_{c,i} = (m_{LF} \cdot Q_{LF,i} + m_{HF} \cdot Q_{HF,i})/(m_{LF} + m_{HF}) \tag{8}$$

$$m_{LF} = \begin{cases} 1, \; if \;\; h < \gamma \\ 1 - (h-\gamma)/(\delta-\gamma)^{N}, \text{ if } \; \gamma \le h < \delta \\ 0, \text{ if } \; h \ge \delta \end{cases} \tag{9}$$

$$m_{HF} = \begin{cases} 0, \text{ if } \; h < \gamma \\ (h-\gamma)/(\delta-\gamma)^{1/N}, \text{ if } \; \gamma \le h < \delta \\ 1, \text{ if } \; h \ge \delta \end{cases} \tag{10}$$

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where m_{LF} and m_{HF}: membership functions for the two local models, $Q_{LF,i}$ and $Q_{HF,i}$: simulated high and low flows for the time step i; γ and δ: threshold for high and for low flows respectively, N: power value used to smooth between the models, the value 1 is given for Type A and 2 or more for Type B. First two optimal specialised models that one for the low-flow ($Q_{HF,i}$) and one for the high-flow ($Q_{HF,i}$) are sought using optimization algarithms and then two membership function parameters δ and γ are introduce to combine specialised models which ruled the transition between the specialised models. The committee model Q_c is calculated by combination sets of δ and γ which are selected within given intervals and the performance measure is calculated by root mean squared error (RMSE) and Nash-Sutcliffe efficiency (NSE) (Nash and Sutcliffe, 1970) which is presented in Appendix A.

3 Results and discussions

The three catchments, namely, Alzette catchment in Luxemburg, Leaf river catchment in USA and Bagmati catchment in Nepal, are selected for case study. The summary statistics and records of data for calibration and verification of catchments are presented in Table 1. The experiment follows the one used in an earlier study (Fenicia et al., 2007) where the Alzette catchment was considered, and only calibration data was considered for building the models without further validation. We present here additional two other catchments (Leaf and Bagmati) with both calibration and verification period and compare the overall model performance when using different weighing schemes for objective functions (Fig. 1) and different membership functions (Fig. 2).

The ranges of model parameters used in optimization of the HBV model are given in Table 2. We produced the local models (high flow and low flow) which are optimized by multi- and single-objective optimization algorithms. The some of the investigated set of parameters from different models are given in Table 4 (Appendix B).

The differently parameterized local models are calibrated by NSGAII, GA and ACCO, and then combined by using various membership functions. In each experiment a

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committee model is compared with the single optimal model which is calibrated by two different single-objective optimization algorithms (GA and ACCO).

The results for the Leaf and Bagmati catchments are presented on Figs. 3 and 4. Interestingly, the committee model is better on both objective functions than the local specialised models for all case studies except Bagmati. For this catchment, the RMSE calculated by single optimal model in verification is 108.60 $m^3 s^{-1}$ and RMSE of the committee model using weighting schemes Type I–III calculated around 106.68–107.75 $m^3 s^{-1}$, however it can be noticeably improved and obtained 104.56 $m^3 s^{-1}$ from the weighting scheme Type IV and membership function B. (see Table 3). In addition we tested a committee model which is built by single optimization of local models separately using ACCO and GA, and compare against single optimal model in Alzette and Leaf catchment.

In Leaf catchment we tested all possible combinations of different weighting schemes types and classes of membership functions. Noticeably, all committee models improved their performances in verification. The RMSE of single model produced 26.76 $m^3 s^{-1}$ in verification period, however when used new types of weighting and membership functions used RMSE dropped to 23.41 $m^3 s^{-1}$. Table 3 reports the performance of committee models and single-optimal models calibrated by ACCO and GA for each catchment. The value of δ and γ shown here is found by optimization of the committee model.

The performances of the committee models which are built from the combination of the two local models for high and low flows with respect to the hydrograph simulations are represented on Fig. 5, It can be observed that the committee model combines the best features of the local models.

Our experiments have lead to the two important observations related to using weighting function for objective functions (Fig. 1 and Eqs. 3–7) in calibration of local models:

– Quadratic function we used earlier (Fenicia et al., 2007) was in fact the first guess that it will reasonably weight different values of flow. In our latest experiments it appeared, quite expectedly, that other function (for example, cubic) may work better in calibration period.

– Dependence on the maximum flow Q_0 becomes a certain problem in operation (verification). This is the maximum for calibration data, but this of course does not guarantee that it will not be superseded in the future when model is in operation (or when simulating operation by using verification data). The quadratic function will still handle values above 1, but if the calibration maximum is exceeded considerably, then the high flow will be given unproportinally high weights, and low flows – unproportianlly low ones.

4 Conclusions and direction for further work

In this study we presented further improvements to a fuzzy committee approach – one possible way to improve the hydrological model prediction involving combination of model outputs obtained by differently parameterized models with the same model structure. The major findings of this study follow:

– Combination of specialised models indeed provides a method leading to the better performance of the resulting committee model.

– On three case studies we could reproduce the situation shown on Fig. 3 when the fuzzy committee model is better on both objective functions than the single model(s).

– The situation of higher performance of a committee model is characteristic to calibration. However, in verification, the results were sometimes mixed (case of Bagmati catchment) and it is not so straightforward to claim that the fuzzy committee model is always better also in verification.

– There is an interesting effect concerning direct optimization of parameters γ and δ. It appeared that in most experiments after optimization these parameters

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obtained very close values which means that there is a very narrow region where local models "work together". Potentially this may lead to situations when a minor change in average flows will force the committee model to produce relatively large changes in outputs. An idea which is tested now is to enforce a wider $[\gamma, \delta]$ range even at the expense of model accuracy on calibration set.

Further development and application of the presented approach is seen in the following. Its application can be extended to coupled modelling system (e.g. Climate change, flood inundation) where hydrological complexity significantly influences whole system (e. g. Hostache et al., 2011). We used same metric of objective functions for different magnitude of flows which are originated from statistical theory. However the nature of this metric (e.g., RMSE) basically oriented for high flows and one might not be suited for low flows. Therefore the performance measure can be acknowledged in the form of transformed metric (e.g. transformed RMSE) to calibrate low flow model (e.g. van Werkhoven et al., 2009; Williwam, 2009; Kollat et al., 2012). Further developments are foreseen in improving the weighting schemes involving hydrological states and various combinations of variables influencing the stream flow (for example those presented by Oudin et al., 2006; Kim et al., 2006; Corzo and Solomatine, 2007a, b; Marshall et al., 2007; Jeong and Kim, 2009). Combining these approaches will lead to techniques for discovering various regimes in the time series representing the modelled system – this would allow for optimal combination of domain (hydrologic) knowledge incorporated in models with the automatic machine learning or time series analysis routines

Appendix A

Performance measure of committee model

The quality of the stimulated discharges from committee models could be assessed by two standard global statistical measures and visual plots of hydrograph in calibration and verification period. In following equations, $Q_{o,i}$: observed discharges for the time

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step i, $Q_{c,i}$: is the simulated discharges for the time step i and n is the number of observations.

1. RMSE (root mean square error) measures the average error between the observed and the simulated discharges from committee model. The closer the RMSE value is to zero which denote the better the performance of the model.

$$\text{RMSE} = \sqrt{\frac{1}{n}\left(\sum_{i=1}^{n}\left(Q_{c,i} - Q_{o,i}\right)^2\right)} \tag{A1}$$

2. NSE (Nash-Sutcliffe efficiency; Nash and Sutcliffe, 1970) measures the one minus absolute squared differences between the simulated discharges from committee model and observed discharges normalized by the variance of the observed discharges. The value of NSE is in the range of $[-\infty, 1]$ and value of one is a perfect fit of model.

$$\text{NSE} = \sqrt{1 - \frac{\sum_{i=1}^{n}\left(Q_{o,i} - Q_{c,i}\right)^2}{\sum_{i=1}^{n}\left(Q_{c,i} - \overline{Q}_{o,i}\right)^2}} \tag{A2}$$

Appendix B

Best set of parameters

The identified set of parameters by different optimization algorithms ACCO, NSGAII, and GA are given in Table 4.

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Acknowledgements. Part of this work was financially supported by the EnviroGRIDS and WeSenseIt projects supported by the FP7 Programme of the European Commission.

References

Abrahart, R. J. and See, L.: Multi-model data fusion for river flow forecasting: an evaluation of six alternative methods based on two contrasting catchments, Hydrol. Earth Syst. Sci., 6, 655–670, doi:10.5194/hess-6-655-2002, 2002.

Anctil, F. and Tape, D. G.: An exploration of artificial neural network rainfall-runoff forecasting combined with wavelet decomposition, J. Environ. Eng. Sci., 3, 121–128, 2004.

Ajami, N. K., Duan, Q., Gao, X., and Sorooshian, S.: Multi-model combination techniques for hydrological forecasting: Application to Distributed Model Inter-comparison Project results, J. Hydrometeorol., 7, 755–768, 2006.

Becker, A. and Kundzewicz, Z. W.: Nonlinear flood routing with multilinear models, Water Resour. Res., 23, 1043–1048, 1987.

Beven, K. J.: Uniqueness of place and process representations in hydrological modelling, Hydrol. Earth Syst. Sci., 4, 203–213, doi:10.5194/hess-4-203-2000, 2000.

Bruen, M.: Black box modelling of catchment behaviour, Ph.D. thesis, National University of Ireland, Dublin, 1985.

Cavadias, G. and Morin, G.: The Combination of Simulated Discharges of Hydrological Models, Application to the WMO Intercomparison of Conceptual Models of Snowmelt Runoff, Nord. Hydrol., 17, 21–32,1986.

Corzo, G. and Solomatine, D. P.: Baseflow separation techniques for modular artificial neural network modelling in flow forecasting, Hydrolog. Sci. J., 52, 491–507, 2007a.

Corzo, G. and Solomatine, D. P.: Knowledge-based modularization and global optimization of artificial neural network models in hydrological forecasting, Neural Networks, 20, 528–536, 2007b.

Cullmann, J., Krauße, T., and Philipp, A.: Enhancing flood forecasting with the help of processed based calibration, Phys. Chem. Earth, 3, 1111–1116, 2008.

Deb, K., Pratap, A., Agarwal, S., and Meyarivan, T.: A Fast and Elitist Multiobjective Genetic Algorithm: NSGA-II, IEEE T. Evolut. Comput., 6, 182–197, 2002.

Fenicia, F., Solomatine, D. P., Savenije, H. H. G., and Matgen, P.: Soft combination of local models in a multi-objective framework, Hydrol. Earth Syst. Sci., 11, 1797–1809, doi:10.5194/hess-11-1797-2007, 2007.

Goldberg, D. E.: Genetic algorithms in search, optimization and machine learning, Reading, MA: Addison-Wesley, 1989.

Hostache, R., Matgen, P., Montanari, A., Montanari, M., Hoffmann, L., and Pfister, L.: Propagation of uncertainties in coupled hydro-meteorological forecasting systems: A stochastic approach for the assessment of the total predictive uncertainty, Atmos. Res., 100, 263–274, 2011.

Jeong, D. I. and Kim, Y.-O.: Combining single-value streamflow forecasts – A review and guidelines for selecting techniques, J. Hydrol., 377, 284–299, 2009.

Juemou, W., Ruifang, Z., and Guanwu, X.: Synthesised Constrained Linear System (SCLS), Beijing, J. Hydraul. Eng., 7, ISSN:0559-9350.0.1987-07-000, 1987.

Keefer, T. N. and McQuivey, R. S.: Multiple linearization flow routing model, J. Hydraul. Div.-ASCE, 100, 1031–1046, 1974.

Kim, Y.-O., Jeong, D., and Ko, I. H.: Combining Rainfall-Runoff Model Outputs for Improving Ensemble Streamflow Prediction, J. Hydrol. Eng., 11, 578–588, 2006.

Kollat, J. B., Reed, P. M., and Wagener, T.: When are multiobjective calibration trade-offs in hydrologic models meaningful?, Water Resour. Res., 48, 3520, doi:10.1029/2011WR011534, 2012.

Lindström, G., Johansson, B., Persson, M., Gardelin, M., and Bergström, S.: Development and test of the distributed HBV-96 hydrological model, J. Hydrol., 201, 272–288, 1997.

Marshall, L., Nott, D., and Sharma, A.: Towards dynamic catch-ment modelling: a Bayesian hierarchical mixture of experts framework, Hydrol. Process., 21, 847–861, 2007.

McLeod, A. I., Noakes, D. J., Hipel, K. W., and Thompstone, R. M.: Combining hydrologic forecast, J. Water Resour. Pl.-ASCE, 113, 29–41, 1987.

Nash, J. E. and Sutcliffe, J. V.: River flow forecasting through conceptual models part I. A discussion of principles, J. Hydrol., 10, 282–290, 1970.

Nasr, A. and Bruen, M.: Development of neuro-fuzzy models to account for temporal and spatial variations in a lumped rainfall-runoff model, J. Hydrol., 349, 277–290, 2008.

Oudin, L., Andréassian, V., Mathevet, T., Perrin, C., and Michel, C.: Dynamic averaging of rainfall-runoff model simulations from complementary model parameterizations, Water Resour. Res., 42, W07410, doi:10.1029/2005WR004636, 2006.

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Shamseldin, A. Y., O'Connor, K. M., and Liang, G. C.: Methods for Combining the Output of Different Rainfall-Runoff Models, J. Hydrol., 197, 203–229, 1997.

Solomatine, D. P.: Two strategies of adaptive cluster covering with descent and their comparison to other algorithms, J. Global Optim., 14, 55–78, 1999.

Solomatine, D. P.: Optimal modularization of learning models in forecasting environmental variables, Proc. of the IEMSs 3rd Biennial Meeting: "Summit on Environmental Modelling and Software", edited by: Voinov, A., Jakeman, A., and Rizzoli, A., Burlington, USA, July 2006.

Solomatine, D. P. and Xue, Y.: M5 model trees compared to neural networks: application to flood forecasting in the upper reach of the Huai River in China, J. Hydrol. Eng., 6, 491–501, 2004.

Todini, E. and Wallis, J. R.: Using CLS for Daily or Longer Period Rainfall-Runoff Modelling, in: Mathematical Models for Surface Water Hydrology, edited by: Ciriani, T. A., Maione, U., and Wallis, J. R., John Wiley & Sons, London, 149–168, 1977.

Toth, E.: Classification of hydro-meteorological conditions and multiple artificial neural networks for streamflow forecasting, Hydrol. Earth Syst. Sci., 13, 1555–1566, doi:10.5194/hess-13-1555-2009, 2009.

van Werkhoven, K., Wagener, T., Reed, P., and Tang, Y.: Senitivity guided reduction of parametric dimensionality for multi-objective calibration of watershed models, Adv. Water Resour., 32, 1154–1169, 2009.

Westerberg, I. K., Guerrero, J.-L., Younger, P. M., Beven, K. J., Seibert, J., Halldin, S., Freer, J. E., and Xu, C.-Y.: Calibration of hydrological models using flow-duration curves, Hydrol. Earth Syst. Sci., 15, 2205–2227, doi:10.5194/hess-15-2205-2011, 2011.

WHO: Intercomparison of Models of Snowmelt Runoff. Operational Hydrology Report No. 23, WHO Report No. 646, World Meteorological Organization, Geneva, Switzerland, 1986

Willems, P.: A time series tool to support the multi-criteria performance evaluation of rainfall-runoff models, Environ. Modell. Softw., 24, 311–321, 2009.

Zhao, R. J.: Flood forecasting method for humid regions of China, East China College of Hydraulic Engineering, Nanjing, China, 1977.

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Table 1. The summary of the runoff data for Alzette catchment in Luxembourg, Leaf catchment in USA, and Bagmati catchment in Nepal.

Statistical properties	Complete data	Calibration data	Verification data
Alzette (Area = 288 km^2)			
Period (day/month/year hour)	29/7/2000 12:00–6/8/2002 07:00 LT	29/7/2000 12:00–6/8/2001 07:00 LT	6/8/2001 08:00–6/8/2002 07:00 LT
Number of data	17720	8960	8760
Average (m^3 s^{-1})	4.64	5.55	3.70
Minimum (m^3 s^{-1})	0.45	0.59	0.45
Maximum (m^3 s^{-1})	51.41	51.41	31.15
Standard deviation (m^3 s^{-1})	5.35	5.52	5.00
Leaf (Area = 1924 km^2)			
Period (day/month/year)	28/7/1951–21/9/1961	28/7/1951–25/7/1957	26/7/1957–21/9/1967
Number of data	3717	2190	1527
Average (m^3 s^{-1})	28.28	23.02	35.81
Minimum (m^3 s^{-1})	1.56	1.56	2.92
Maximum (m^3 s^{-1})	2.38	549.35	1313.91
Standard deviation (m^3 s^{-1})	64.48	47.37	82.51
Bagmati (Area = 3500 km^2)			
Period (day/month/year)	1/1/1988–31/12/1995	1/1/1988–30/6/1993	1/7/1994–31/12/1995
Number of data	2922	1940	922
Average (m^3 s^{-1})	150.0	140.16	179.17
Minimum (m^3 s^{-1})	5.1	5.1	6.7
Maximum (m^3 s^{-1})	5030.0	3040	5030
Standard deviation (m^3 s^{-1})	271.2	226.42	350.83

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Table 2. The ranges of model parameters.

		Ranges used in calibration (optimization)		
Parameter	Description	Alzette	Leaf	Bagmati
FC	Maximum soil moisture content	100–450	100–400	50–500
LP	Limit for potential evapotranspiration	0.3–1	0.1	0.3–1
ALFA	Response box parameter	0.1–1	0–2	0–4
BETA	Exponential parameter in soil routine	0.1–2	1.0–4	1.0–6
K	Recession coefficient for upper tank	0.005–0.5	0.05–0.5	0.05–0.5
K4	Recession coefficient for lower tank	0.001–0.1	0.01–0.3	0.01–0.3
PERC	Percolation from upper to lower response box	0.01–1	0–5	0–8
CFLUX	Maximum value of capillary flow	0–0.05	0–1	0–1
MAXBAS	Transfer function parameter	8 15	2 6	1 3

Table 3. The performances of single optimal models and committee models (RMSE and NSE) of various catchments. The bold values stand for best performance of committee models.

		Weighted function		Membership function			RMSE		NSE	
Catchments	Models	Type	N	Type	δ	γ	Calibration	Verification	Calibration	Verification
Alzette	Qs(ACCO)	–					2.3697	2.393	0.8158	0.8133
	Qs(GA)	–					2.3095	2.419	0.8253	0.7656
	Qc(NSGAII)	I	2	A	0.5	0.3	1.9911	2.0688	0.8698	0.8285
	Qc(ACCO)	I	2	A	0.5	0.25	2.0984	2.0586	0.8557	0.8302
	Qc(GA)	I	2	A	0.6	0.4	2.1894	2.1489	0.8427	0.7789
Leaf	Qs(ACCO)	–					17.56	26.76	0.866	0.899
	Qs(GA)	–					17.36	26.58	0.883	0.910
	Qc(ACCO)	I	2	A	0.39	0.37	15.63	25.23	0.894	0.910
		II	2	A	0.45	0.44	16.01	24.38	0.888	0.916
		III	2	A	0.65	0.14	15.60	24.52	0.894	0.915
		IV	2	A	0.56	0.55	16.20	25.68	0.886	0.906
		I	**2**	**B**	**0.39**	**0.38**	**15.63**	**25.26**	**0.894**	**0.910**
		II	2	B	0.45	0.44	16.03	24.38	0.888	0.916
		III	2	B	0.94	0.15	15.67	24.72	0.893	0.913
		IV	2	B	0.56	0.55	16.20	25.68	0.886	0.906
	Qc(GA)	**I**	**2**	**A**	**0.51**	**0.5**	**15.76**	**24.88**	**0.892**	**0.912**
		II	2	A	0.66	0.14	16.13	25.81	0.887	0.905
		III	2	A	0.99	0.16	16.53	24.67	0.881	0.914
		IV	2	A	0.99	0.3	16.60	23.96	0.880	0.919
		I	2	B	0.99	0.15	16.30	25.56	0.884	0.907
		II	2	B	0.87	0.16	16.22	25.58	0.885	0.907
		III	2	B	0.99	0.31	16.47	24.34	0.882	0.916
		IV	2	B	0.99	0.42	16.55	24.06	0.881	0.918
		I	1	B	0.42	0.41	15.96	24.04	0.889	0.918
		I	3	B	0.99	0.23	16.50	25.53	0.881	0.908
	Qc(NSGAII)	I	2	A	0.5	0.49	16.05	23.86	0.888	0.919
		II	**2**	**A**	**0.5**	**0.49**	**15.71**	**23.85**	**0.892**	**0.919**
		III	2	A	0.86	0.47	17.36	23.41	0.869	0.922
		IV	2	A	0.86	0.45	16.76	23.97	0.878	0.919
		I	2	B	0.5	0.29	16.45	23.96	0.883	0.919
		II	2	B	0.5	0.15	16.71	23.95	0.892	0.919
		III	2	B	0.99	0.49	17.29	23.46	0.870	0.922
		IV	2	B	0.99	0.46	16.71	23.97	0.878	0.919
		I	1	A	0.38	0.36	16.58	23.86	0.880	0.919
		I	**3**	**A**	**0.5**	**0.49**	**15.96**	**23.79**	**0.889**	**0.920**
Bagmati	Qs(ACCO)	–					101.20	108.60	0.873	0.828
	Qs(GA)	–					103.35	110.53	0.868	0.817
	Qc(NSGAII)	I	2	A	0.62	0.53	94.22	107.58	0.867	0.824
		I	3	A	0.6	0.42	93.70	107.24	0.888	0.825
		II	3	A	0.55	0.5	93.53	106.61	0.889	0.827
		III	3	A	0.6	0.3	92.67	107.75	0.891	0.823
		IV	2	A	0.61	0.52	90.91	105.40	0.895	0.837
		IV	**2**	**B**	**0.62**	**0.54**	**90.90**	**104.56**	**0.895**	**0.859**

The value of $\alpha = 0.75$ used in weighting schemes Type II, III and IV.

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Table 4. The some identified set of parameters by different optimization algorithms.

		Pars	FC	LP	ALFA	BETA	K	K4	PERC	CFLUX	MAXBAS
Alzette	ACCO	SO	284.83	0.26	0.06	0.65	0.02	0.01	0.16	0.04	10.96
		LF	356.34	0.46	0.1	0.42	0.02	0	0.14	0.1	13.48
		HF	414.48	0.19	0.3	0.49	0	0.03	0.97	0.01	8.51
	GA	SO	309.97	0.35	0.03	0.72	0.03	0.01	0.27	0.01	11.45
		LF	255.11	0.46	0.07	0.98	0.03	0.01	0.23	0.05	12.62
		HF	338.84	0.56	0.06	0.95	0.01	0.02	0.89	0	8.37
	NSGA-II	LF	253.24	0.16	0.07	0.54	0.02	0	0.13	0	9.49
		HF	253.25	0.34	0.07	0.52	0.02	0.01	0.14	0	9.54
Leaf	ACCO	SO	272.11	0.29	0.3	1.57	0.27	0.26	2.27	0.62	6.04
	NSGA-II	LF	301.88	0.36	0.37	1.95	0.14	0.24	1.07	0.89	5.57
		HF	274.26	0.9	0.45	2.27	0.15	0.26	1.24	0.85	5.86
Bagmati	ACCO	SO	354.98	0.71	0.17	1	0.28	0.08	8	0	2.55
	NSGA-II	LF	419.58	0.76	0.15	1.01	0.35	0.07	7.99	0.03	2.49
		HF	419.63	0.62	0.1	1.11	0.42	0.25	7.66	0.04	2.92

SO: single optimal model; LF: low flow model; HF: high flow model.

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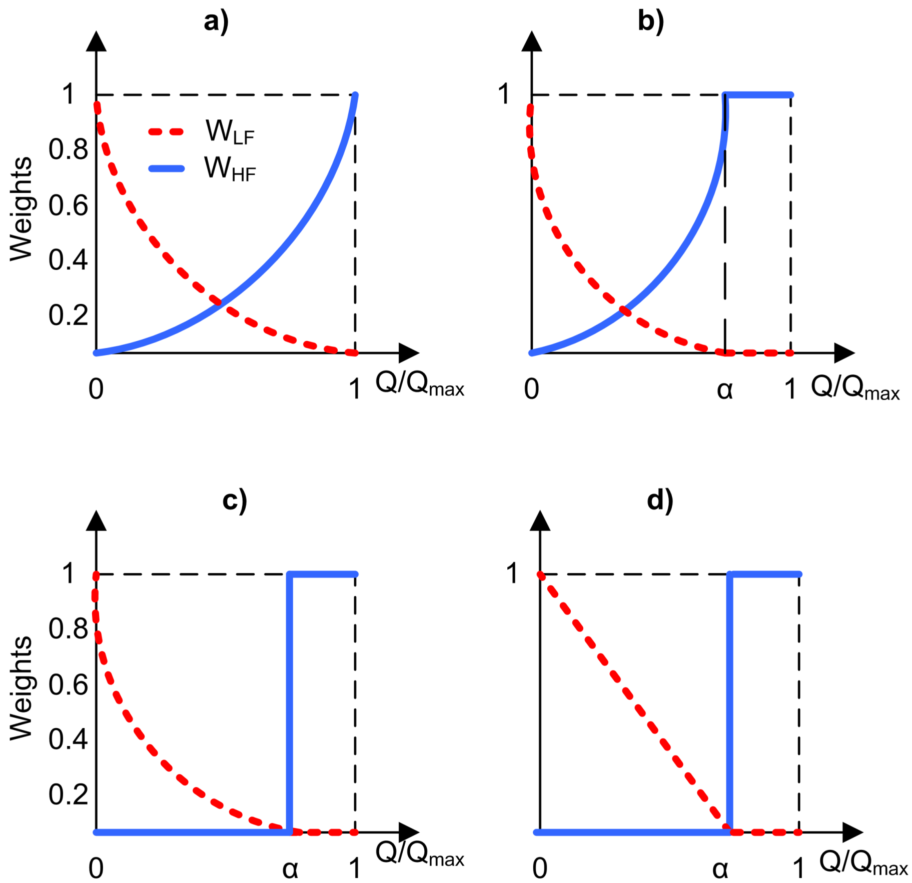

Fig. 1. **(a)** Type-I, -weighting scheme for objective functions studied in Fenicia et al. (2007). **(b)** Type-II, **(c)** Type-III, and **(d)** Type-IV; additional these three weighting schemes attempted in the latest experiments.

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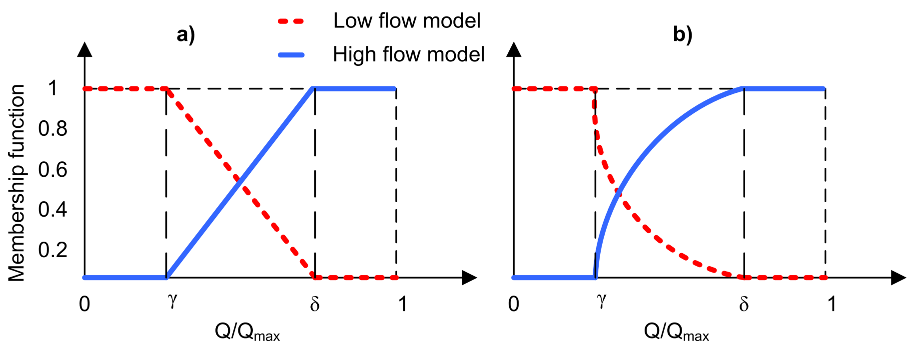

Fig. 2. (a) A typical fuzzy membership function used to combine the local models (Type A), **(b)** a class of membership functions for high and low flow models tested in the new experiments (Type B).

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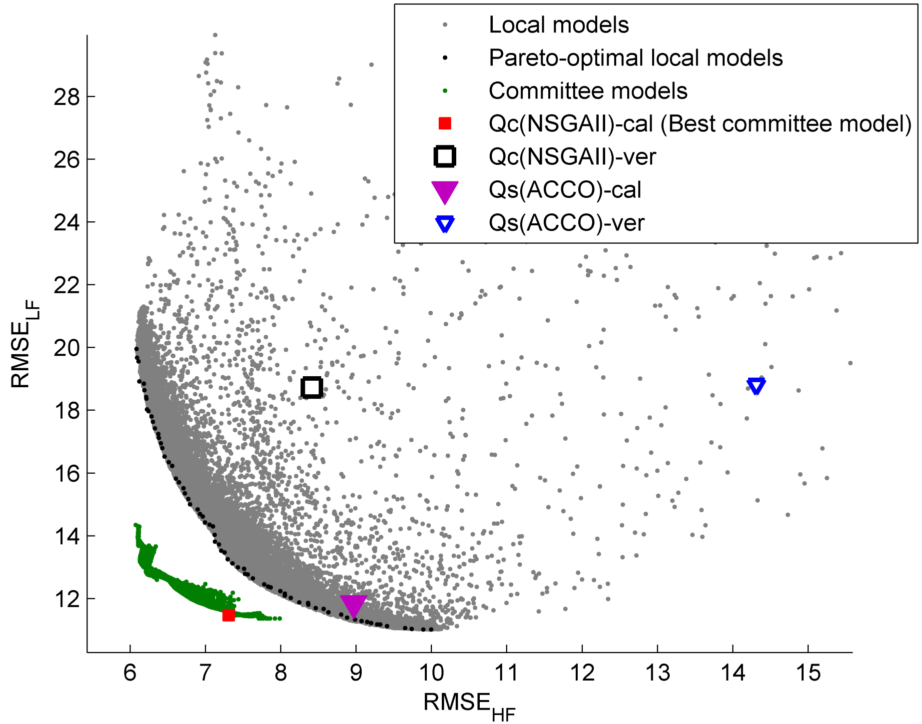

Fig. 3. The identified sets of Pareto-optimal parameterisations of local models, committee models and optimal global models (optimization by NSGAII), and optimal global (single) models calibrated by ACCO in Leaf catchment. The objective functions values for the test data set are shown as well, where Q_c – committee model, Q_s – single optimal model, cal – calibration and ver – verification.

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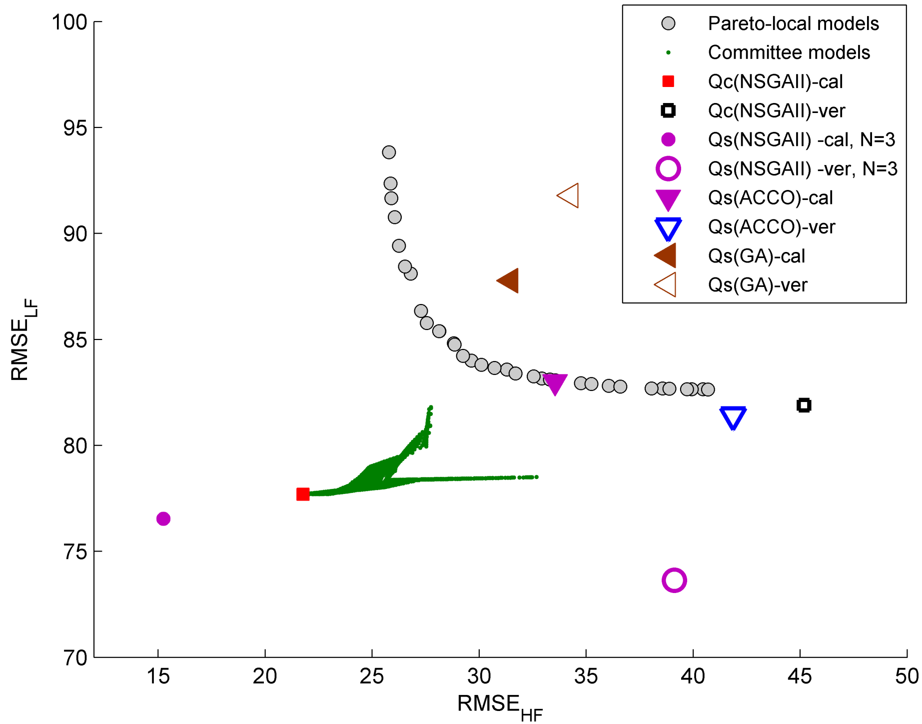

Fig. 4. The identified sets of Pareto-optimal parameterisations of local models, committee models (optimization by NSGAII), and optimal global (single) models calibrated by ACCO and GA in Bagmati catchment.

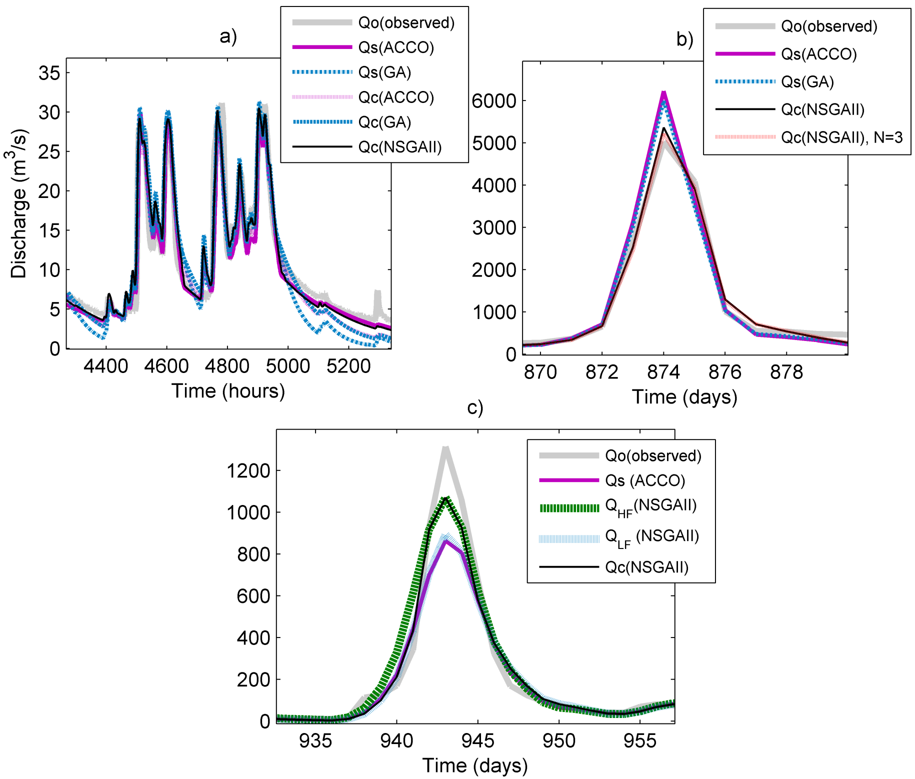

Fig. 5. A fragment of hydrograph generated from various models, Q_o – observed discharge, Q_s – model identified by single optimization (ACCO and GA), Q_c – committee model (ACCO, GA and NSGAII), N – power value used in weighted scheme of objective functions ($N = 2$ – quadratic (default) and $N = 3$ – cubic), $Q_{HF(LF)}$ – high and low flow, **(a)** Alzette (31 January 2002 08:00:00 – 18 March 2002 03:00:00), **(b)** Bagmati (20 May 1990–28 May 1990), and **(c)** Leaf (13 February 1960–8 March 1960).

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