Risks in hydrological modelling due to uncertainties in discharge determination

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Abstract Uncertainties in discharge determination may have serious consequences for hydrological modelling and resulting discharge predictions affecting flood and drought risk assessment and decision making. The aim of this study is to quantify the effect of discharge errors on parameters and performance of a conceptual hydrological model for discharge prediction applied to two catchments. Four error sources in discharge determination are considered: a combination of systematic and random measurement errors without autocorrelation; random measurement errors with autocorrelation; hysteresis in the discharge-water level relation; and effects of an outdated discharge–water level relation. Results show that systematic errors and an outdated discharge–water level relation have a considerable influence on model performance, while other error sources have a small to negligible effect. The effects of errors on parameters are large if the effects on model performance are large, and *vice versa*. Parameters controlling the water balance are influenced by systematic errors, and parameters related to the shape of the hydrograph are influenced by random errors. Large effects of discharge errors on model performance and parameters should be taken into account when using discharge predictions for risk assessment and decision making.

Key words uncertainty; discharge determination; hydrological modelling; model calibration; SCEM-UA; Meuse River

INTRODUCTION

Hydrological models are usually calibrated using discharge time series observed at one or a few locations in the river basin, using time series of observed precipitation and other climatological variables as input. Errors in observed time series may result in errors in estimated parameters during calibration and hence an increased uncertainty in simulated discharge. This may seriously affect flood and drought risk assessment and decision making. The effect of sampling errors, spatial resolution, and quality of precipitation input on model parameters and performance has been frequently investigated (e.g. Bárdossy & Das, 2008; Booij, 2002; Andréassian *et al.*, 2001, respectively). However, the effect of errors in discharge determination on model parameters and model performance has been studied less often, a few exceptions being Aronica *et al.* (2006) and McMillan *et al.* (2010). More insight in these effects can direct future discharge determination methods and research, and may improve short- and long-term discharge predictions supporting flood and drought risk management.

The aim of this study is to quantify the effect of discharge errors on the performance and parameters of a conceptual hydrological model for discharge prediction. The study area consists of two catchments in the Meuse River basin in Belgium, France and Luxembourg. The hydrological model HBV to simulate river discharge, the calibration procedure, the errors in discharge time series and the implementation of error sources in adapted discharge time series are subsequently described. Finally, results are discussed and conclusions drawn.

STUDY AREA

The Meuse River basin is located in France, Belgium, Luxembourg, Germany and the Netherlands. In this study the focus is on two catchments in the Meuse basin: the Ourthe (1597 km^2) in Belgium and the Chiers (2207 km^2) in Luxembourg, Belgium and France. The average slope of the Ourthe is larger than the slope of the Chiers and this is reflected in a more extreme high and low flow behaviour of the Ourthe. Mean annual precipitation is 971 mm for the

Ourthe and 918 mm for the Chiers and mean annual discharge is 438 and 380 mm, respectively (period 1968–1998, see Booij & Krol, 2010).

Daily precipitation, temperature, potential evapotranspiration and discharge data for the period 1968–1997 are used. Potential evapotranspiration has been calculated using the Penman-Monteith equation. The precipitation, temperature and potential evapotranspiration series are corrected for elevation and prepared for the two catchments using data provided by KMI (Belgian Royal Meteorological Institute) and Météo France, similar to Booij (2005). The discharge series have been obtained from SETHY/WACONDAH (Belgium) and DIREN Lorraine (France).

METHODS

HBV hydrological model

For river discharge simulation, the hydrological model HBV of the Swedish Meteorological and Hydrological Institute (SMHI) is used (Bergström, 1995). This model is a semi-distributed, conceptual hydrological model using sub-catchments as the primary hydrological units. It takes into account area-elevation distribution and basic land-use categories (glaciers, forest, open areas and lakes). HBV uses readily available data (precipitation, potential evapotranspiration and temperature) as inputs and has proven capabilities in simulating large river basins. The large number of applications using this model, under various physiographic and climatological conditions, has shown that its structure is very robust and general, in spite of its relative simplicity (e.g. Lidén & Harlin, 2000; Dong *et al.*, 2005; Akhtar *et al.*, 2009). There are several parameters included in the model which have to be estimated through calibration with observed data. The model consists of six routines, which are a precipitation accounting routine, a soil moisture routine, a quick runoff routine and a base flow routine, which together transform excess water from the soil moisture zone to local runoff, a transformation function and a routing routine.

The HBV model has been recently applied to the Meuse basin (Booij, 2005; Leander *et al.*, 2005; Ashagrie *et al.*, 2006; Leander & Buishand, 2007, Van Pelt *et al.*, 2009; Booij & Krol, 2010) and specifically to the Ourthe catchment (Berne *et al.*, 2005; Driessen *et al.*, 2010). The HBV model schematization of Booij & Krol (2010) is used in this study. In this schematization, the Meuse basin is subdivided into 15 catchments, including the Ourthe and Chiers catchments.

Calibration procedure

Model calibration is carried out using the SCEM-UA algorithm (Vrugt *et al.*, 2003). SCEM-UA is an automatic global searching method which is based on the SCE-UA algorithm (Duan *et al.*, 1992). Instead of using the Downhill Simplex method that is used in the SCE-UA algorithm, an evolutionary Markov Chain Monte Carlo (MCMC) sampler is used. This means that a controlled random search is used to find the optimum set of parameter values in the parameter space. The choice for the SCEM-UA method is based on the fact that it is an automatic global search method that converges quite fast to the optimal value. An advantage of this algorithm is that the chance of finding the global optimum is very high. First a calibration is performed with eight HBV parameters requiring 4000 iterations. Parameter ranges are taken from Booij & Krol (2010). Next, a sensitivity analysis is performed to determine the most important five parameters which are used in subsequent calibrations. The other parameters get default values.

Model performance is evaluated using a combined objective function Y (Akhtar *et al.*, 2009):

$$Y = \frac{NS}{1 + |RVE|} \tag{1}$$

where NS is the Nash-Sutcliffe coefficient and RVE the relative volume error (a fraction). For an acceptable model performance, NS should be close to 1 and RVE should be close to 0 resulting in a Y value close to 1. The calibration period is from 1984 to 1998 and the validation period is from 1968 to 1983. The model is calibrated for the original and each of the adapted discharge series using SCEM-UA.

Errors in discharge time series

Uncertainties in discharge time series are present due to errors in discharge determination. Two types of errors are distinguished: measurement errors and errors in the relation between discharge and water level (*Q–h* relation) used in discharge determination. Measurement errors can occur in the determination of the water level, cross-section and/or velocity. These errors can have several causes: uncertainties in measured data, uncertainties regarding the executing of the measurement and uncertainties regarding the performance of the measuring equipment. This results in systematic errors or random errors (with or without correlation) or a combination of both. Errors in the *Q–h* relation are caused by the properties of high water events (e.g. shape and gradient), hysteresis effects and outdated *Q–h* relations. An outdated *Q–h* relation can be caused by changes in the cross-section of the river resulting in systematic errors. For example, if sedimentation takes place at a certain location, the water level will be higher for a certain discharge compared to the water level before sedimentation.

Error sources in adapted discharge time series

In reality, combinations of errors occur in discharge determination. Four error sources in discharge determination are considered. Error sources 1 and 2 represent errors in discharge measurements, and error sources 3 and 4 represent errors in the *Q–h* relation. Source 1 is a combination of systematic and random measurement errors without autocorrelation, source 2 includes random measurement errors with autocorrelation, source 3 comprises errors in the *Q–h* relation caused by the properties of high water events and hysteresis effects and source 4 covers effects of an outdated *Q–h* relation.

Adapted discharge time series incorporating these error sources are constructed by stochastically disturbing the original observed discharge time series. Random errors (without autocorrelation) are incorporated by randomly adjusting the original time series with values drawn from a normal distribution with zero mean and a standard deviation of 2.5% and 5% of the original discharge value (two scenarios). Systematic errors are implemented by adding a constant relative value to the original time series (six scenarios: –25%, –10%, –5%, 5%, 10% and 25%). Random errors with autocorrelation are incorporated using the method of De Kok & Booij (2009). Errors in the *Q–h* relation due to the properties of high water events are included by adapting the original time series depending on the shape of the high water event. Errors in the *Q–h* relation due to hysteresis effects are generated using different flood wave celerities (five scenarios: 0.7, 1.1, 1.5, 1.9 and 2.3 m/s) following Jansen *et al*. (1979, p. 75). Effects of an outdated *Q–h* relation are simulated by adding a gradually increasing systematic error to the original time series. This systematic error starts to increase just after a revision of the *Q–h* relation and reaches its maximum just before a new revision. The systematic errors are assumed to be absolute deviations from the original values (four scenarios: maximum systematic errors are 1, 5, 10 and 15 m^3/s), because it is assumed that the expiration of the *Q–h* relation is caused by changes in the cross-section. Furthermore, it is assumed that the systematic errors are positive and that the *Q–h* relation is revised every 5 years (see Jansen, 2007).

Quality of adapted discharge time series

The quality of the adapted discharge time series is assessed using two quality functions. These functions can be used to compare the quality of the discharge series with the objective function after calibration. The first function considers the quality of the shape of the hydrograph and is comparable with the Nash-Sutcliffe coefficient. This function is called Quality Of Discharge (*QOD*) and is shown in equation (2). A perfect match of the original and adapted time series will result in a value of 1 for this function:

$$QOD = 1 - \frac{\sum_{i=1}^{N} \left[Q_a(i) - Q_o(i)\right]^2}{\sum_{i=1}^{N} \left[Q_o(i) - \overline{Q_o}\right]^2} \tag{2}$$

where Q_a is the adapted discharge, Q_o is the original discharge, i is the time step and N is the total number of time steps. The second function looks at the difference in water balance between the original and adapted discharge series and is called *BALANCE*. It has an optimal value of 0.

$$BALANCE = \frac{\sum_{i=1}^{N}\left[Q_a(i) - Q_o(i)\right]}{\sum_{i=1}^{N}\left[Q_o(i)\right]} \tag{3}$$

The *QOD* and *BALANCE* functions are based on similar quality functions for rainfall time series (*GORE* and *BALANCE*) introduced by Andréassian *et al.* (2001).

RESULTS AND DISCUSSION

Model performance and parameters for original discharge time series

Table 1 presents the model performance for the Ourthe and Chiers using the original discharge time series for calibration and validation. The objective function value *Y* is very good for the Outhe in the calibration and still good in the validation. Values for the Chiers are smaller, but comparable in the calibration and validation. For the Chiers, a total of 5.5 years (instead of 16 years) has been used in the validation due to limited data availability. These results are similar to the results of Booij & Krol (2010) when comparing similar evaluation periods.

Table 1 Model performance for Ourthe and Chiers catchments using original discharge time series for calibration and validation.

Catchment	Calibration			Validation		
	NS	RVE (%)	Y	NS	RVE (%)	Y
Ourthe	0.93	0.0	0.93	0.85	0.9	0.84
Chiers	0.77	0.0	0.77	0.79	4.4	0.75

In the Ourthe catchment, the HBV model parameters *FC*, *ALFA* and *KF* have a strong convergence at the beginning of the calibration and therefore are well identifiable, while the optimizing algorithm seems to have more difficulties in determining *BETA* and *LP*. In the Chiers catchment, *FC*, *BETA* and *LP* show a strong convergence and thus are well identifiable, while *ALFA* and *KF* show a weaker convergence and are less identifiable.

Model performance for adapted discharge time series

Results show that systematic errors and an outdated *Q–h* relation have a considerable influence on model performance, while random errors with autocorrelation have some influence and the other error sources have a negligible effect. As an example, the influence of a combination of systematic and random measurement errors without autocorrelation (source 1) represented by the two quality functions on the objective function *Y* is shown in Fig. 1 for the Ourthe. The different symbols represent different systematic errors (triangle: 5%, circle: 10%, square: 25%) with a 2.5% standard deviation for the random error, where a dot represents a (corresponding) 5% standard deviation for the random error. The "*" symbol indicates the objective function in the original situation with optimal values of 1 and 0 for *QOD* and *BALANCE*, respectively. Figure 1 shows that the influence of systematic errors is indeed considerable, and the influence of random errors is small. The relation between *BALANCE* and *Y* shows that a small positive systematic error results in a slightly larger value of *Y* compared to the original discharge series. Similar results are found for the Chiers.

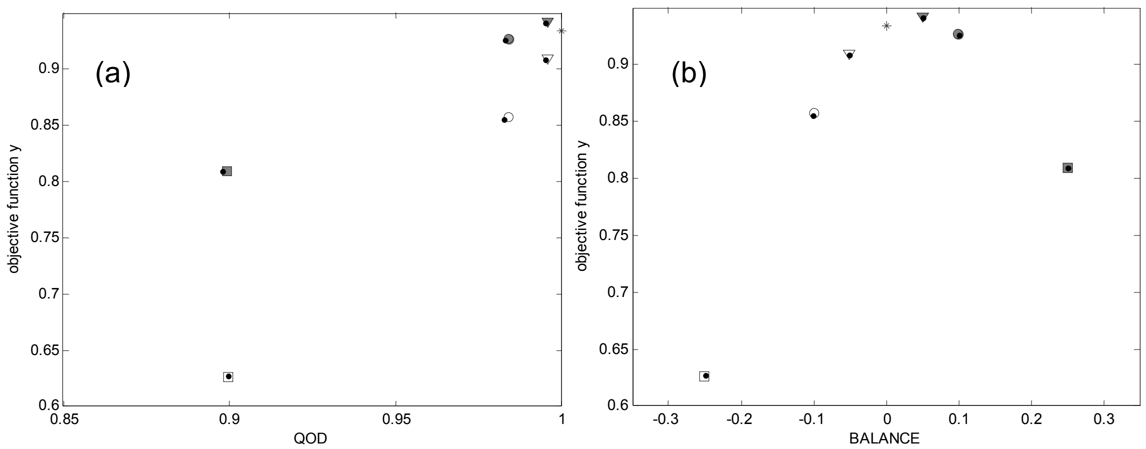

Fig. 1 Relation between quality functions (a) *QOD* and (b) *BALANCE* and objective function *Y* for Ourthe.

Model parameters for adapted discharge time series

Results show that the effects of errors on parameters are large if the effects on model performance are also large, and *vice versa*. As an example, the influence of error source 1 on the parameters is shown in Fig. 2 for the Ourthe. The different symbols represent different systematic errors (triangle: 5%, circle: 10%, square: 25%), where an open symbol indicates a negative systematic error and a filled symbol indicates a positive one. Because of the small influence of random errors, these symbols are used for both standard deviations of 2.5% and 5%. The "*" indicates the objective function and parameter value in the original situation. Parameters controlling the water balance are influenced by systematic errors and parameters related to the shape of the hydrograph are influenced by random errors. The water balance parameters show a certain pattern in both catchments. The values of *FC* and *BETA* increase if the systematic error is negative, while the values decrease with a positive systematic error. A similar but opposite behaviour is found for *LP*. The observed patterns can be explained by the physical meaning of the parameters. For instance *FC*, representing the capacity of the soil moisture reservoir, decreases with a positive systematic error, because the model has to generate more runoff than in the original situation during the entire calibration period.

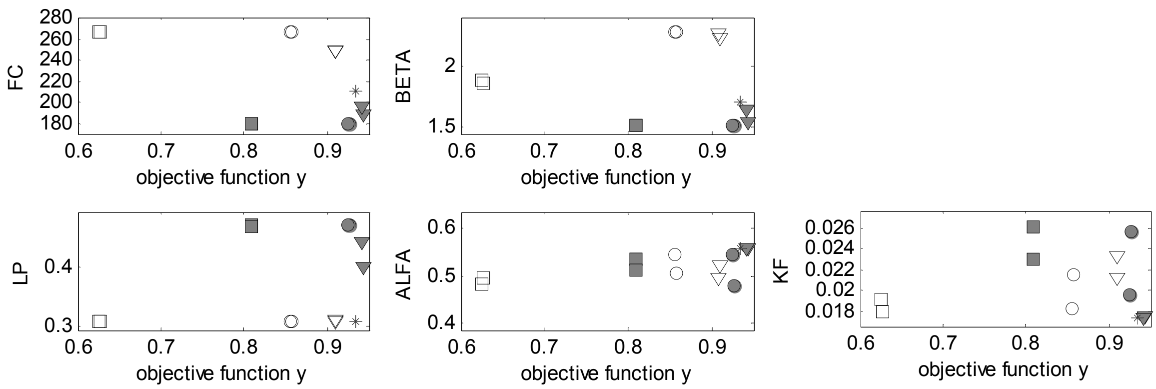

Fig. 2 Relation between objective function *Y* and HBV model parameters for the Ourthe.

CONCLUSIONS

The aim of this study was to quantify the effect of discharge errors on the performance and parameters of a conceptual hydrological model. Systematic errors and an outdated discharge–water level relation have a considerable influence on model performance, while random errors with autocorrelation have some influence and the other error sources have a negligible effect. The effects of errors on parameters are large if the effects on model performance are also large and *vice versa*. Parameters controlling the water balance are influenced by systematic errors and parameters related to the shape of the hydrograph are influenced by random errors. The effects of errors do not vary much between the catchments. Large effects of discharge errors on model performance and parameters should be taken into account when using discharge predictions for risk assessment and decision making.

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