Impact of uncertainties in discharge determination on the parameter estimation and performance of a hydrological model

Sander P. M. van den Tillaart, Martijn J. Booij and Maarten S. Krol

ABSTRACT

Uncertainties in discharge determination may have serious consequences for hydrological modelling and resulting discharge predictions used for flood forecasting, climate change impact assessment and reservoir operation. 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. Six error sources in discharge determination are considered: random measurement errors without autocorrelation; random measurement errors with autocorrelation; systematic relative measurement errors; systematic absolute measurement errors; hysteresis in the discharge–water level relation and effects of an outdated discharge–water level relation. Assuming realistic magnitudes for each error source, results show that systematic errors and an outdated discharge–water level relation have a considerable influence on model performance, while other error sources have a small to negligible effect.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 as well 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 flood forecasting and impact assessment.

Key words | discharge determination, hydrological modelling, Meuse River, model calibration, rating curve, uncertainty

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INTRODUCTION

Hydrological models usually are calibrated using discharge time series observed at one or a few locations in a river basin and 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 discharge predictions used for flood forecasting (Cloke & Pappenberger 2009), climate change impact assessment (Booij 2005; Minville *et al*. 2008) and reservoir operation (Verbunt *et al.* 2005), for example. The effect of sampling errors, spatial resolution and quality of precipitation input on model parameters and performance has been frequently investigated (e.g., Andréassian *et al*. 2001; Booij 2002; Bárdossy & Das 2008, respectively). However, the effect of errors in discharge determination on model parameters and model performance has been less often studied. The discharge is usually estimated by measuring river stages and converting these to river discharge using a rating curve. Errors in river stage measurements and the rating curve will result in errors in discharge determination. Uncertainties in rating curves have been investigated in many studies, already summarised in a review by Pelletier (1988) and recently quantified by, for example, Moyeed & Clark (2005),

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Pappenberger *et al.* (2006) and Di Baldassarre & Montanari (2009). For example, Di Baldassarre & Montanari (2009) estimated rating curve uncertainty based on hydraulic simulations with a one-dimensional hydraulic model. Results showed that errors in river discharge data are significant and can have a large impact on the output of hydrological and hydraulic models. In particular, errors in peak discharges may be large due to the extrapolation of the rating curve beyond the largest gauged discharge (Lang *et al.* 2010; Mathevet & Garçon 2010; Jalbert *et al.* 2011).

Effects of errors in discharge determination on hydrological models have been assessed in a few studies. Montanari (2004) quantified the different sources of uncertainty and propagated them through the river discharge estimation procedure to obtain the uncertainty in estimated discharge. A simulation study with synthetic data was then performed to assess the impact of these uncertain discharges on the parameters and performance of the model. Aronica *et al.* (2006) studied the influence of errors in the rating curve on the output uncertainty of a daily conceptual linear-nonlinear rainfall–runoff model using the GLUE (generalized likelihood uncertainty estimation) procedure. McMillan *et al.* (2010) presented a methodology to estimate a complete probability density function of the discharge for a given water level measurement. This uncertainty information is explicitly taken into account in the model calibration procedure. Their results show that this explicit incorporation of observed discharge uncertainty leads to improved discharge predictions of the distributed rainfall–runoff model.

The aim of this study is to quantify the effect of errors in discharge determination on the performance and parameters of a conceptual hydrological model for discharge prediction. The study builds upon the work done in the previous studies in different ways. First, the different sources of uncertainty in discharge determination are separately quantified and several scenarios are constructed for each source to assess the sensitivity of model parameters and performance to individual uncertainty sources. Previous studies assessed the influence of all uncertainty sources in discharge determination together on model performance and parameters (e.g., McMillan *et al.* 2010) or the influence of part of the uncertainty sources (Aronica *et al.* 2006). Second, the scenarios are constructed in such a way that a broad range of uncertainty values is incorporated including rather extreme ones. This enables a comparison of the effect of a very well-gauged catchment on the hydrological model behaviour and the effects of poor or almost ungauged catchments on hydrological models. This is very relevant in the context of the Prediction in Ungauged Basins (PUB) decade initiated by the International Association of Hydrologic Sciences (Sivapalan *et al.* 2003). Third, we consider two catchments in the Meuse River basin in Belgium, France and Luxembourg with different geographical characteristics and different initial model performances (Booij & Krol 2010), where previous studies focused on one single catchment. The study of two catchments may reveal the dependence of the results on characteristics and modelling potential of these two catchments.

The paper is organised as follows. First, the study area and data are described. Next, the methodology is presented including the hydrological model to simulate river discharge, the calibration procedure, the errors in discharge time series and the implementation of error sources in adapted discharge time series. Then, the results are presented and discussed and finally conclusions are drawn.

STUDY AREA AND DATA

The Meuse basin is located in France, Belgium, Germany, Luxembourg and the Netherlands. In this study, two catchments in the Meuse basin are considered: the Ourthe (surface area of 1,597 km^2) in Belgium and the Chiers (surface area of 2,207 km^2) in France, Belgium and Luxembourg (see Figure 1). The average slope of the Ourthe (0.004) is larger than the slope of the Chiers (0.001) and this is reflected in a more extreme high and low flow behaviour of the Ourthe, i.e., the ratio of the average annual maximum and average annual minimum discharge is 85.4 for the Ourthe and 12.9 for the Chiers for the period 1968–1998. 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, potential evapotranspiration, temperature and discharge data for the period 1968–1998 are used. Potential evapotranspiration has been calculated using the Penman–Monteith equation. The precipitation,

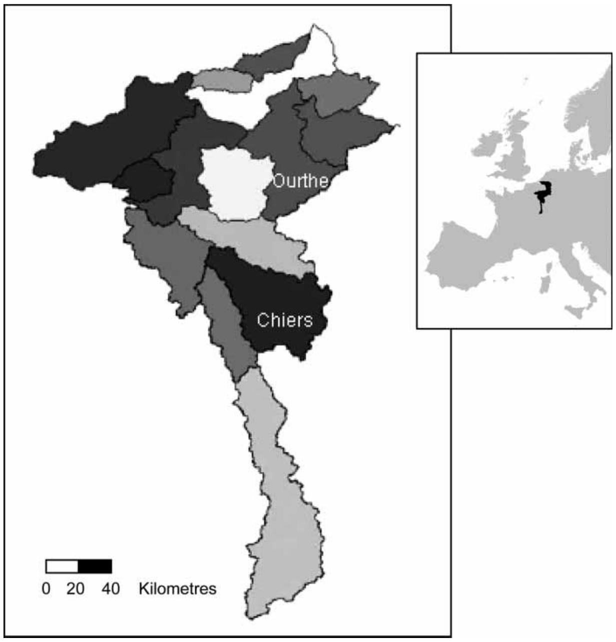

Figure 1 | Location of the Meuse River basin in Western Europe and schematisation of the Meuse River basin upstream of Borgharen in HBV-15 with catchments Ourthe and Chiers.

potential evapotranspiration and temperature series have been corrected for elevation and prepared for the two catchments using data provided by Météo France and KMI (Belgian Royal Meteorological Institute), similarly to Booij (2005). The discharge series have been obtained from DIREN Lorraine (France) and SETHY/WACONDAH (Belgium).

METHODOLOGY

Hydrological model

For river discharge simulation, the hydrological model HBV (Hydrologiska Byråns Vattenbalansavdelning) of the Swedish Meteorological and Hydrological Institute (SMHI) is used (Bergström & Forsman 1973; Bergström 1995). This model is a semi-distributed, conceptual hydrological model using sub-catchments as primary hydrological units. It takes into account area–elevation distribution and basic land use categories (forest, open areas, lakes and glaciers). 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). The model consists of a precipitation routine representing rainfall, snow accumulation and snow melt, a soil moisture routine determining actual evapotranspiration and overland and subsurface flow, a fast flow routine representing overland flow, a slow flow routine representing subsurface flow, a transformation routine for flow delay and attenuation and a routing routine for river flow (Bergström 1995). A detailed description of the most recent version of HBV (HBV96) can be found in Lindström *et al.* (1997). In Table 1, the HBV model parameters are described and representative parameter ranges from Deckers *et al.* (2010) are given.

The HBV model has recently been 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 schematisation of Booij & Krol (2010) is used in this study. In this schematisation, the Meuse basin is subdivided into 15 catchments including the Ourthe and Chiers catchments, and each catchment is simulated in a lumped way.

Table 1 | HBV model parameters and their minimum (min) and maximum (max) values from Deckers *et al.* (2010)

Parameter	Description	Min	Max
FC	Maximum soil moisture storage (mm)	125	800
BETA	Parameter of power relationship to simulate indirect runoff (–)	1	4
LP	Limit above which evapotranspiration reaches its potential value (–)	0.1	1
ALFA	Measure for non-linearity of flow in quick runoff reservoir (–)	0.1	3
KF	Recession coefficient for runoff from quick runoff reservoir (day^{-1})	0.0005	0.15
KS	Recession coefficient for runoff from base flow reservoir (day^{-1})	0.0005	0.15
PERC	Constant percolation rate occurring when water is available (mm day^{-1})	0.1	2.5
CFLUX	Maximum value for capillary flow (mm day^{-1})	0.1	2.5

Calibration procedure

Model calibration is carried out using the Shuffled Complex Evolution Metropolis (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, which 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 optimal 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 which converges relatively fast to the optimal parameter set. 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 (see Table 1) requiring 4,000 iterations. Parameter ranges from Deckers *et al.* (2010) are taken. Next, a sensitivity analysis is performed to determine the most important parameters resulting in five parameters (*FC*, *LP*, *BETA*, *ALFA* and *KF*) showing considerably more sensitivity of the objective function to varying parameter values. These five parameters are used in subsequent calibrations. The other parameters get default values from SMHI (2003), i.e., $KS = 0.005$ day^{-1}, $PERC = 1.0$ mm day^{-1} and $CFLUX = 1.0$ mm day^{-1}.

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 (Nash & Sutcliffe 1970) 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. This combined objective function Y is used since NS alone would not guarantee a good model performance for the water balance (as discussed by, for example, Gupta *et al.* 2009) and one single (combined) objective function is preferred here. 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, and performance is tested on the original series in both calibration and validation periods.

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 (rating curve) used in discharge determination (Venetis 1970; McMillan *et al.* 2010). 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 rating curve are caused by the properties of high water events, hysteresis effects and outdated rating curves. Properties of high water waves differ depending on the shape and gradient of the wave. Steep and short high water waves will result in an underestimation of the discharge when applying the rating curve, while long and gradually increasing waves will cause an overestimation of the discharge due to the steepness of the wave. Hysteresis effects occur because the discharge at a certain water level is higher if the water level is increasing, than in case the water level is decreasing compared to the equilibrium situation (Jansen *et al.* 1979). An outdated rating curve can be caused by changes in the cross section of the river, for instance due to vegetation growth or bed form changes 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. Here, six individual error sources in discharge determination are considered as shown in Table 2. 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 5, 10

Table 2 | Error sources in discharge determination

Source	Type	Nature	
1	Discharge measurement errors	Random	Without autocorrelation
2	Discharge measurement errors	Random	With autocorrelation
3	Discharge measurement errors	Systematic	Relative
4	Discharge measurement errors	Systematic	Absolute
5	Errors in rating curve	Properties of high water events and hysteresis effects	
6	Errors in rating curve	Outdated rating curve	

and 15% of the original discharge value (totalling 30 scenarios). Random errors with autocorrelation are incorporated using the method of De Kok & Booij (2009)

$$Q_a(t) = Q_o(t) + \varepsilon(t) \quad (2)$$

$$\varepsilon(t) = \delta(t)Q_o(t) + \alpha\varepsilon(t - \Delta t) \quad (3)$$

where Q_a is the adapted discharge, Q_o is the original discharge, t is the time step, ε is the noise term, δ is a randomly time-varying scaling factor, α is an autocorrelation coefficient and Δt is the temporal resolution (1 day). The time-varying scaling factor δ is uniformly distributed in the interval $[-D, D]$, where D can have values between 0 and 1. In this research, a fixed value for D of 0.05 is used, because in this case the maximum spread of the random errors will be around 10% as observed for the Meuse River (Jansen 2007). Since information on the quality of discharge (QOD) data for the Ourthe and Chiers was not available, quality information for the Meuse River has been used. The autocorrelation coefficient α is unknown for the Ourthe and Chiers and therefore several values are used: 0.5, 0.7, 0.8, 0.9 and 0.95 (totalling 30 scenarios).

Systematic errors are implemented by adding a constant relative value to the original time series (28 scenarios: ±1, 2, 3, 4, 5, 6, 7.5, 10, 12.5, 15, 17.5, 20, 22.5 and 25%) and by adding a constant absolute value to the original time series (20 scenarios: ±5, 10, 15, 20, 25, 30, 35, 40, 45 and 50% of the average discharge).

Errors in the rating curve 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. An overestimation of the discharge is simulated if a gradually increasing wave is present, i.e., if the discharge is above the threshold of a high water level (450 and 280% of the average discharge for the Ourthe and Chiers, respectively) and if the increase or decrease of the water level is smaller than the maximum gradient of the gradually increasing wave (two scenarios for both catchments: about 20 and 40% of the average discharge per day). An underestimation of the discharge is simulated if there is a high peak with a large increase, i.e., if the discharge is higher than the threshold of the peak of the wave (900 and 560% of the average discharge for the Ourthe and Chiers, respectively) and the gradient is larger than the minimal gradient of the steep wave (two scenarios for both catchments: about 60 and 80% of the average discharge per day). Two scenarios for the simulation of underestimation (80 and 90% of the original discharge values) and two scenarios for the simulation of overestimation (110 and 120% of the original discharge values) are used for both catchments. This results in eight scenarios for errors due to the properties of high water events for each catchment: four scenarios for overestimation (10 and 20%) for two scenarios for the maximum gradient (20 and 40% of the average discharge) and similarly four scenarios for underestimation. Errors in the rating curve 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). More information on rating curves for unsteady flows can be found in, for example, Fenton & Keller (2001) and Dottori *et al.* (2009).

Effects of an outdated rating curve are simulated by adding a gradually increasing systematic error to the original time series. The magnitude of this systematic error starts to increase just after a revision of the rating curve and reaches its maximum just before a new revision. The systematic errors are assumed to be absolute deviations from the original values, because it is assumed that the expiration of the rating curve is caused by changes in the cross section. Furthermore, it is assumed that the systematic errors are positive or negative for a particular run and that the rating curve is revised every 5 years (see Jansen 2007). Twenty maximum systematic errors are randomly drawn from a uniform distribution between 0 and 60% of the average discharge or 0 and −60% of the average discharge. An illustration of the adapted discharge time series for different error sources compared to the original discharge time series is shown in Figure 2.

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 and to compare the effects of different error sources with different characteristics (e.g., random vs. systematic, relative vs. absolute, uncorrelated vs. correlated) on the model performance. The first function considers the quality of the shape of the hydrograph and is comparable with the NS coefficient. This function is called *QOD* and is shown in Equation (4). A perfect match of the original and adapted time series will result in a value of 1 for this function

$$QOD = 1 - \frac{\sum_{t=1}^{N}[Q_a(t) - Q_o(t)]^2}{\sum_{t=1}^{N}\left[Q_o(t) - \overline{Q_o}\right]^2} \quad (4)$$

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

$$BALANCE = \frac{\sum_{t=1}^{N}[Q_a(t) - Q_o(t)]^2}{\sum_{t=1}^{N}[Q_o(t)]} \quad (5)$$

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 3 presents the model performance for the Ourthe and Chiers catchments using the original discharge time series for

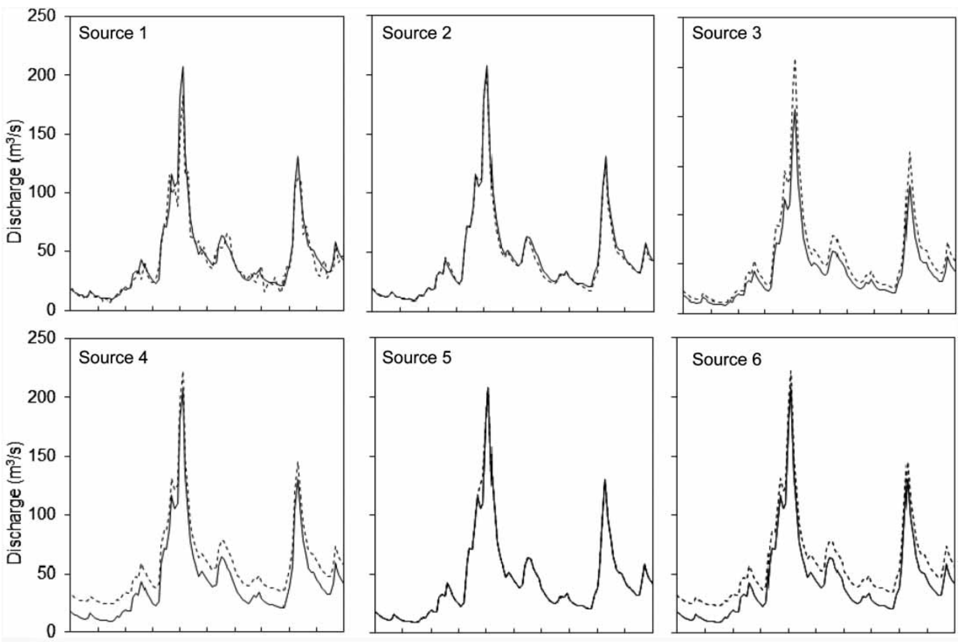

Figure 2 | Illustration of adapted discharge time series (dashed line) for error source 1 (standard deviation = 15%), 2 (autocorrelation coefficient = 0.95), 3 (relative error = 25%), 4 (absolute error = 50% of the average discharge), 5 (maximum gradient of the gradually increasing wave = 40% of the average discharge per day and overestimation is 20%) and 6 (maximum absolute error = 60% of the average discharge, revision in January 1998) compared to original discharge series (straight line) for the Ourthe for the period October–December 1998.

Table 3 | Model performance for Ourthe and Chiers catchments using original discharge time series for calibration and validation

	Calibration			Validation		
Catchment	***NS***	***RVE*** **(%)**	**Y**	***NS***	***RVE*** **(%)**	**Y**
Ourthe	0.94	0.0	0.94	0.85	0.9	0.85
Chiers	0.77	0.0	0.77	0.79	4.7	0.75

calibration and validation. The objective function value *Y* is very good for the Ourthe 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. The only exception is the calibration period for the Chiers, where Booij and Krol obtained a significantly lower value for the NS coefficient (0.68 in the validation). This can be caused by differences between the studies in objective functions and calibration procedures.

Model performance for adapted discharge time series

Figure 3 shows the influence of each error source represented by the two quality functions on the objective function *Y* for the Ourthe and the Chiers for the calibration period. The figure shows that systematic errors (relative and absolute, i.e., error sources 3 and 4) and an outdated rating curve (error source 6) have a considerable influence on model performance, while random errors with autocorrelation (error source 2) have some influence and the other

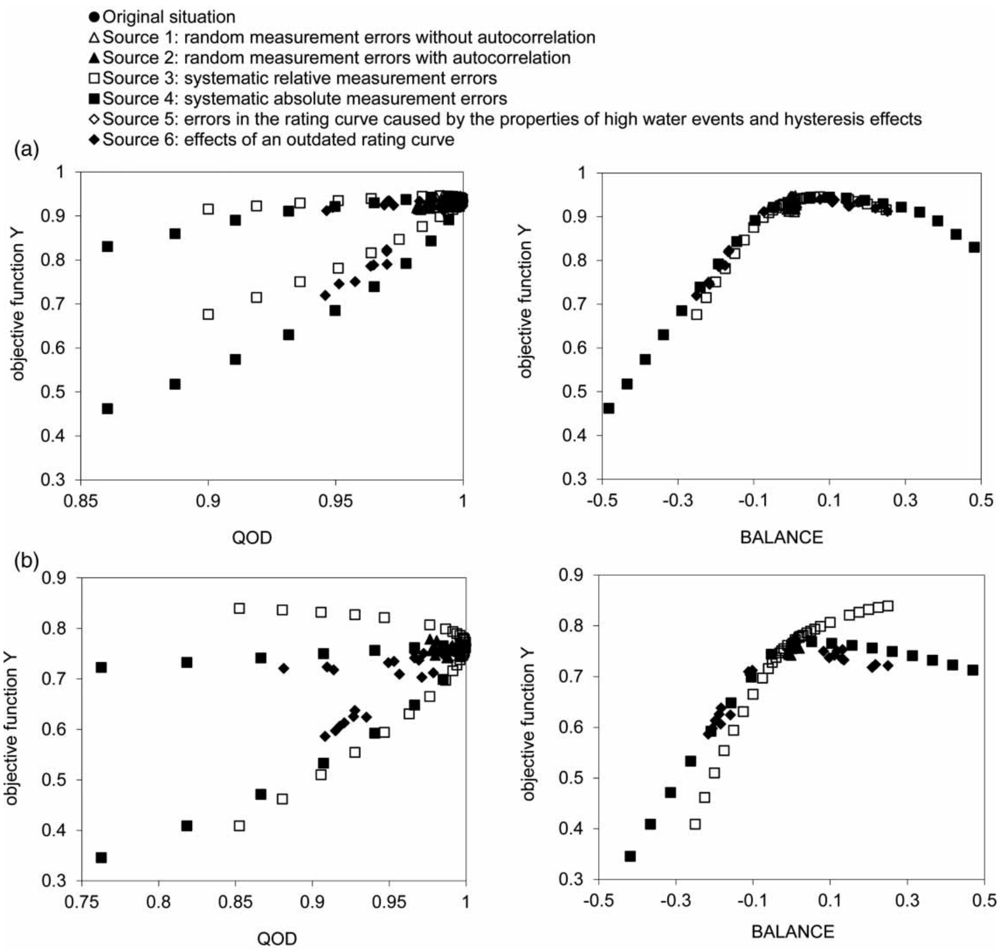

Figure 3 | Effect of error sources on relations between quality functions *QOD* and *BALANCE*, and objective function *Y* for (a) Ourthe and (b) Chiers.

error sources (1 and 5) have a negligible effect. We will further focus on the effects of systematic relative errors on model performance and parameters because of their importance and similarity with systematic absolute errors and outdated rating curves. The influence of systematic relative measurement errors represented by the two quality functions on the objective function Y in both catchments is shown in Figure 4 for *QOD* and Figure 5 for *BALANCE* for the calibration and validation period. The '*' sign indicates the objective function in the original situation with optimal values of 1 and 0 for *QOD* and *BALANCE*, respectively. The relations between *BALANCE* and Y show that a (small) positive systematic error results in a slightly larger value of Y compared to the original discharge series for

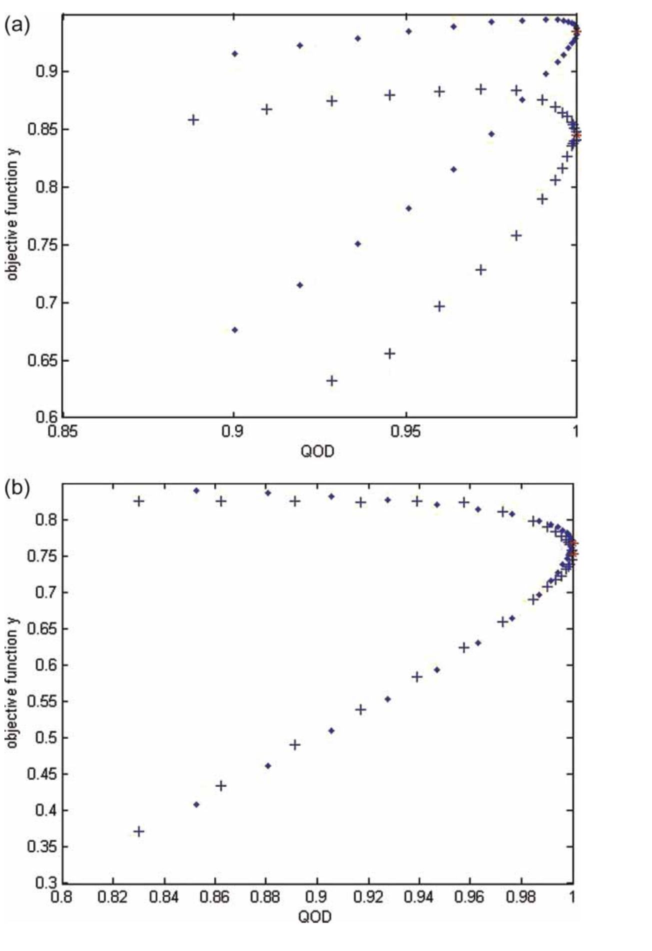

Figure 4 | Relation between quality function *QOD* and objective function *Y* for (a) Ourthe and (b) Chiers for systematic relative errors for calibration (points) and validation (crosses).

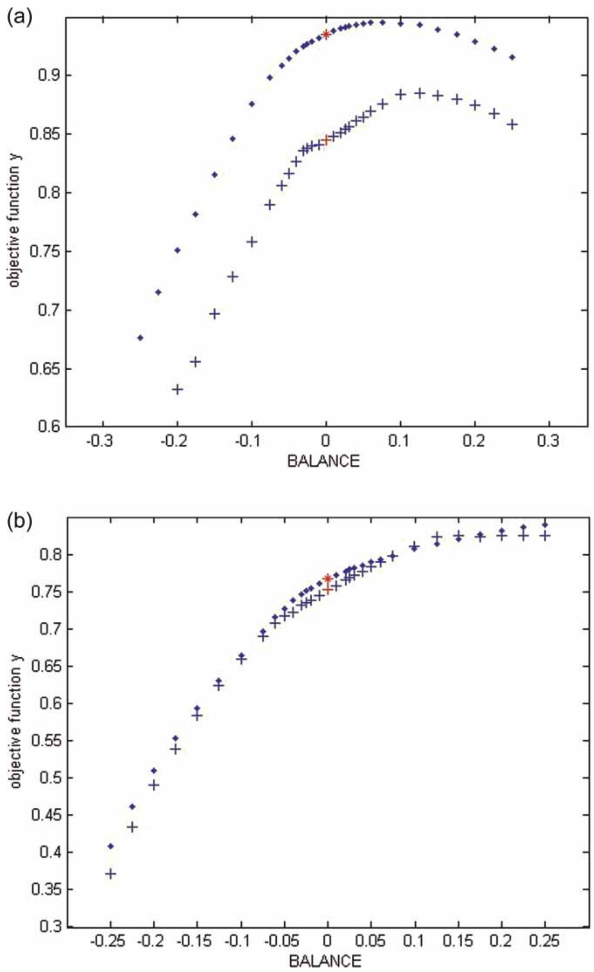

Figure 5 | Relation between quality function *BALANCE* and objective function *Y* for (a) Ourthe and (b) Chiers for systematic relative errors for calibration (points) and validation (crosses).

the Ourthe and, in particular, for the Chiers. In general, positive systematic errors result in a better model performance than (the same) negative systematic errors. This behaviour is similar for the Ourthe and Chiers, although ranges of the objective function differ between the two catchments. The improvement of the model performance for positive errors in the observed discharge might be related to errors in the measured input by an overestimation of the precipitation and/or an underestimation of the potential evapotranspiration. Also unknown inter-catchment groundwater flows might cause this behaviour; see, for example, Le Moine *et al.* (2007) and Herron & Croke (2009). This effect is more prominent for the Chiers, which might be related to the lower model performance for this catchment in the calibration compared to the performance for the Ourthe. The relations between the quality functions and the objective function are similar for the calibration and validation, although the objective function values for the Ourthe are significantly lower in the validation compared to the calibration as has already been observed in Table 1.

The analyses have been repeated using synthetic data for systematic relative measurement errors. The synthetic data are the simulated discharge series with an optimum parameter set for each catchment assuming to represent the measured discharge series. Such an analysis might reveal how much the results are affected by model structural errors. Results are found to be very similar to the results in Figures 4 and 5. Most important differences are obviously the perfect *Y* values in the original situation for the synthetic data as compared to the measured data and the absence of positive systematic errors resulting in a slightly larger value of *Y* compared to the original discharge series. Therefore, we conclude that the results are not significantly affected by model structural errors.

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 large as well and vice versa. Figure 6 shows the influence of systematic relative measurement errors on the uncertainty in model parameters due to calibration for the Ourthe and Chiers. The uncertainty is represented by error bars which include all parameter values resulting in objective function values within 5% of the optimum model performance (optimum *Y* value). Parameters controlling the water balance are influenced by systematic errors and parameters related to the shape of the hydrograph are influenced by random errors, although to a lesser extent. The water balance parameters show a certain pattern in both catchments. The values of *FC* 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. Although parameter uncertainties are considerable, this behaviour can be clearly observed with more distinct patterns for *LP* for the Ourthe and *FC* for the Chiers than for *FC* for the Ourthe and *LP* for the Chiers. The third water balance parameter *BETA* shows a less clear pattern, probably because it is more indirectly influencing the water balance. The relation between *ALFA* and *KF* on the one hand and *Y* on the other hand is less pronounced and different for the two catchments. The expected increase of both parameters with increasing systematic errors (i.e., becoming less negative or more positive) is partly observed for the Chiers, although *KF* values decrease again for small positive errors. The relations between parameter values and systematic relative errors are partly influenced by the selected ranges for the parameters, in particular by the lower limits of *ALFA* and *LP*. These ranges have been selected based on the ranges of Deckers *et al.* (2010), who in turn, based their ranges on a number of well-known HBV studies. However, the lower limits for these parameters (both equal to 0.1) are very close to their physical minimum values (both equal to 0) and therefore are not expected to have a large influence on the results.

CONCLUSIONS

The aim of this study was to quantify the effect of discharge errors on the performance and parameters of a conceptual hydrological model. Assuming realistic magnitudes for each error source in the two catchments, results show that systematic relative and absolute errors and an outdated rating curve 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 large as well 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 two catchments with different geographical characteristics. The

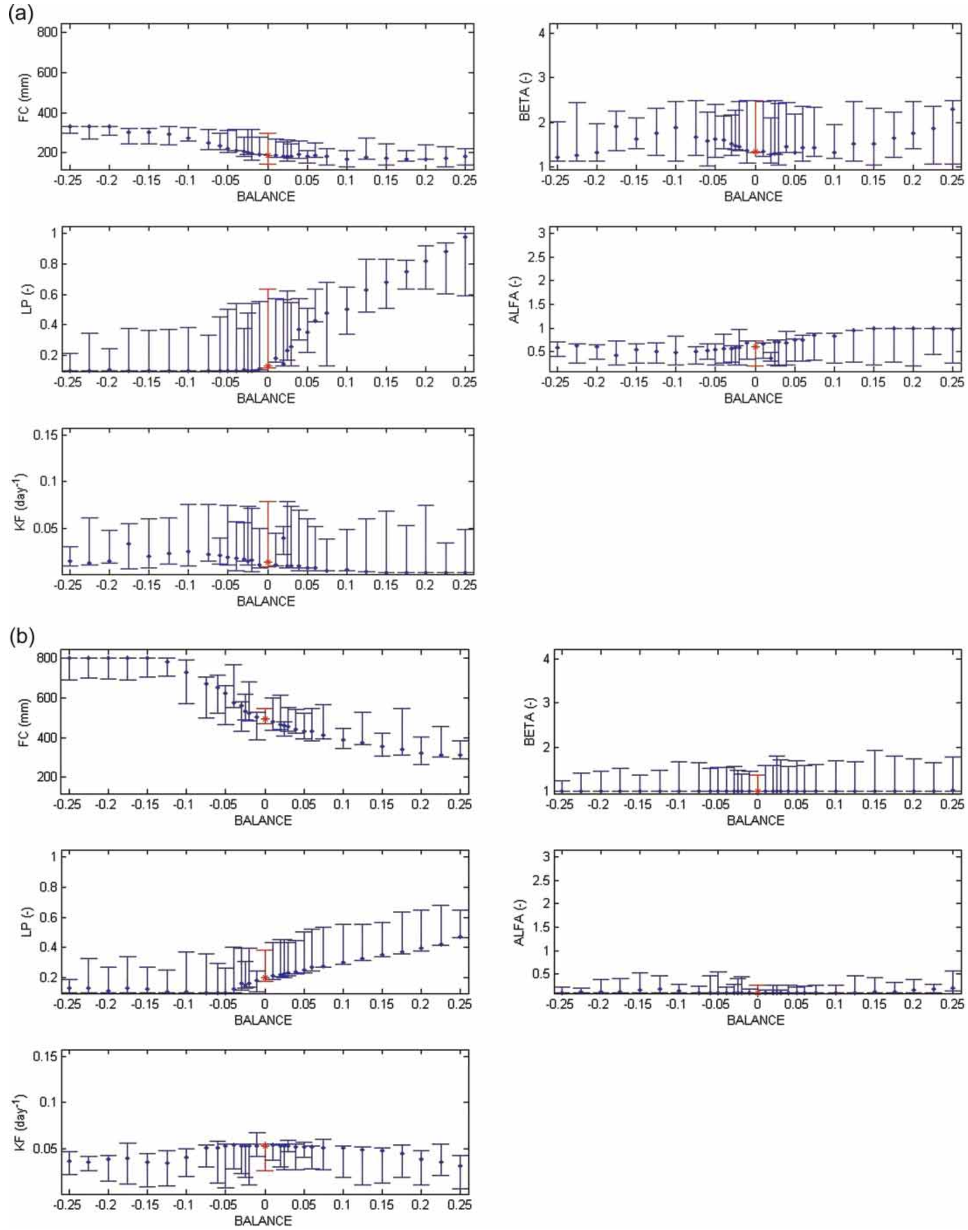

Figure 6 | Relation between quality function *BALANCE* and uncertainty in HBV model parameters due to calibration for (a) Ourthe and (b) Chiers for systematic relative errors. The uncertainty is represented by error bars which include all parameter values resulting in objective function values within 5% of the optimum model performance (optimum *Y* value). The error bar for *BALANCE* = 0 is the parameter uncertainty in the original situation.

initial model performance for both catchments, i.e., the model performance using the original discharge series for calibration, has some influence on the relations between errors and discharge quality functions. The relations for the Ourthe, with a higher initial model performance, are generally more pronounced and show less uncertainty due to calibration than the relations for the Chiers. In this study, one conceptual hydrological model has been used. However, we think that the effects of discharge errors on model performance will be similar for other conceptual hydrological models, i.e., the relatively large influence of systematic errors in the discharge determination on the model performance compared to random errors and errors affecting only a small part of the hydrograph (e.g., discharge peaks). Obviously, the influence of discharge errors on parameters is model specific, although different effects on parameters influencing the water balance compared to parameters influencing the hydrograph shape will probably also be found for other models. Models including functions to deal with catchments with non-conservative water balance behaviour due to, for instance, deep groundwater losses (see, for example, Le Moine *et al.* 2007; Goswami & O'Connor 2010) could partly compensate for the (structural) errors, and consequently effects of discharge errors will be smaller.

Large effects of discharge errors on model performance and parameters should be taken into account when using discharge predictions for flood forecasting, climate change impact assessment and related decision-making, for example. Moreover, more insight into these effects can direct future discharge determination methods and related research. The more extreme scenarios for the individual uncertainty sources, in particular for systematic errors and outdated rating curves, give an indication of the effect of poorly gauged or ungauged catchments on model parameters and performance relevant for the PUB initiative (Sivapalan *et al.* 2003). These effects can be considerable, for instance, a relative systematic error of 20% could result in a model performance decrease of up to 25% and similar changes in parameters. This obviously could lead to a wrong conceptualisation of the hydrological processes important for the transformation of rainfall to runoff with potentially severe consequences when applying the model for forecasting and long-term prediction purposes. All the more, these insights emphasise the importance of more and improved discharge measurements, but also the need for alternative discharge measurements in poorly gauged catchments by, for example, using satellite data (Koblinsky *et al.* 1993; Xu 2004; Sun *et al.* 2010).

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