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Highlights of the paper ''Data errors and hydrological modelling: reducing uncertainty in flood risk assessment''

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We show the relevance of uncertainty in river flow data

We illustrate how data uncertainty may undermine the reliability of hydrological predictions

We show that the effect of data uncertainty on hydrological model should be carefully evaluated

We propose promising solutions to reduce data uncertainty and its impact

Data errors and hydrological modelling: reducing uncertainty in flood risk studies

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Abstract

Data uncertainty is more and more recognised as a serious issue, potentially undermining the reliability of many hydrological analyses and flood risk studies. Indeed, recent contributions show that river flow observations are affected by errors that frequently reach 25% even when best measurement techniques are adopted. Despite the above problem, there is still little guidance by the literature on modelling strategies to be adopted under observation errors. This paper shows how the effect of data uncertainty on hydrological modelling is difficult to predict by simply relying on intuition, common sense and expert knowledge. In particular, we argue there is a need for developing best modelling practices to help practitioners in mitigating the effect of erroneous observations. We show that sensitivity analysis, optimal choice of model complexity and selective calibration can play a very important role in this respect.

Keywords: data uncertainty, monitoring techniques, hydrological modelling, flood risk

1. Introduction

Over the past two decades, hydrologists have devoted much attention to uncertainty estimation, by also analysing the impact of observation errors on hydrological modelling and flood risk assessment [1-4]. In fact, uncertainty estimation is one of the key research targets of the PUB (Prediction in Ungauged Basins) initiative of the International Association of Hydrological Sciences (IAHS) [5]. In particular, in the past few years data uncertainty has gained increasing attention, being its impact on global hydrological uncertainty more and more recognised. For instance, [6] and [7] introduced the term “disinformative data” to indicate erroneous observations that falsify the inference of water balance dynamics. They noted that this problem has received little attention so far.

As far as river discharge observations is concerned, best practices for measuring river flow are summarised by [8]. A first extensive review of contributions dealing with the quantitative assessment of the uncertainty in river flow data was proposed by [9], who concluded that uncertainty in discharge observation varies in the range 8%-20% at the 95% confidence level, depending on the monitoring technique that is used. Later on, more "optimistic" authors [10] reported smaller errors (5-6%), but they neglected many important sources of inaccuracy [11].

Recently, The World Meteorological Organisation (WMO) updated the “WMO Manual for Stream Gauging” [12]. In Chapter 10, which is devoted to uncertainty of discharge measurements, it is stated that for observations obtained with the velocity-area method “....it is not possible to provide absolute guidelines for making the qualitative evaluation of accuracy. As a general rule, the accuracy of most discharge measurements will be about 5%, or qualitatively a good measurement. This is sometimes used as the baseline accuracy, with accuracy upgraded to

excellent when measuring conditions are significantly better than average, and accuracy downgraded to fair or poor when conditions are significantly worse than average". When river flows are retrieved by using the rating curve method, uncertainty is normally expected to increase. In fact, [13] reported errors up to 25% at the 95% confidence level, confirming the findings of [9]. More details on the velocity-area method and the rating curve method for river flow measurement can be found [12, 13].

A relevant matter of concern is the effect of this observation uncertainty on hydrological studies. It is expected that errors of such amount can induce significant uncertainty in flood risk assessment and engineering design. For instance, it was found that accounting for precipitation errors during hydrologic model calibration significantly affects the posterior distribution of the watershed model parameters and the uncertainty of model predictions [14].

The purpose of this paper is to illustrate the practical effects of data uncertainty on hydrological analysis, by inspecting to what extent river flow errors can affect hydrological modelling and flood risk assessment. Secondly, we indicate some potential ways forward to reduce this type of uncertainty in hydrological monitoring and mitigating its effect on hydrological modelling. More specifically, we argue that innovative monitoring techniques and an appropriate selection of hydrological model structure and calibration strategy can significantly contribute to reduce the impact of data uncertainty on hydrological studies.

2. Impact of observation uncertainty on flood risk studies

The uncertainty in river discharge observations affects many steps of the assessment of flood risk, such as the estimation of the so-called design flood (i.e. the discharge value corresponding to a given recurrence interval or return period), which is often underestimated (if not neglected) in applied hydrology and flood risk studies. Indeed, a number of authors investigated the

uncertainty in the design flood caused by imprecision of the river flow data [11, 15-17]. For instance, [15,16] examined the effect of errors in river discharge data on flood frequency analysis and proposed an inference framework, which makes explicit allowance for observation errors. More specifically, [16] showed that errors induced on design flood estimation by the extrapolation of the rating curve can "very substantially, indeed massively" corrupt the estimation of the design flood. However, [16] concluded that a better characterisation of the errors induced by the rating curve is needed to obtain a more precise estimation. More recently, [17] developed a novel methodology for evaluating the joint impact of sample variability and rating curve imprecision on design flood estimation. Yet, they did not take into account the additional uncertainty in river discharge observations induced by extrapolating the rating curve, which is often the main source of error in flood data. Also, [18] used a Bayesian framework including a multiplicative error on the rating curve to assess the influence of errors in discharge data on the outcomes of flood frequency analysis.

More recently, [11] investigated the impact of river flow data errors on the uncertainty of design floods by using different error structures, proposed by the scientific literature. A first analysis focused on the extrapolation error and used the error structure proposed by [16]. According to this error model, [11] found that a systematic underestimation or overestimation of the design flood is introduced by the extrapolation of the rating curve. A second analysis was based on the assumption that observation errors are Gaussian with zero mean and standard deviation proportional to the true river discharge and it was showed that the effect of this type of error, although conservative for design purposes, may also lead to relevant uncertainty in the estimation of design floods. Finally, a third analysis was performed by using the results of [13] for the characterization of the global uncertainty in flood data. The results of this study showed

that the design flood estimation may be seriously affected by errors in flood data, especially when these are systematic.

Moreover, uncertainty in river flow data is also one of the main sources of inaccuracy in flood hazard mapping. In order to illustrate this issue, we performed a hydraulic exercise on a 35 km reach of the Po River, the Italian longest river with a contributing area at the closure section of about 70000 km^2. The model code LISFLOOD-FP [19] was used to simulate the June 2008 flood inundation in a 98 km reach of the Po River, between Boretto and Borgoforte (Italy).

Figure 1 shows the impact of the uncertainty of hydrological data on flood hazard mapping. In particular, the first flood extent map shows the areas that were simulated as inundated (Figure 1, left). This first map was obtained by neglecting the uncertainty in hydrological data and therefore using the observed hydrograph in Boretto as upstream boundary condition. Conversely, the second map (Figure 1, right) was built by explicitly considering the river flow uncertainty. To this end, an ensemble of hydrographs in Boretto was obtained by assuming the error model derived, for the same river reach, by [13]. The ensemble simulations were then combined to generate an uncertain inundation map showing the ensemble chance, i.e. the percentage of time in which each pixel was simulated as flooded. The map shows the 5th, 50th and 95th percentile and clearly illustrate the relevant impact of observation uncertainty in flood inundation mapping.

Thus, data uncertainty does play a significant role in flood risk studies, by affecting flood frequency analysis and flood risk mapping and therefore need to be better considered. In particular, there is a need to derive clear guidelines on how to mitigate its impact. The next sections of this paper provide some first attempts.

3. Reducing the impact of observation uncertainty on the calibration of hydrological models

The actual impact of observation errors on hydrological modelling has been poorly investigated so far. Actually, although common sense suggests that data error can seriously undermine the reliability of hydrological simulations, little guidance exists on the best modelling practices to be followed. The literature dedicated ample room to the comparison of the performances of different models (lumped versus distributed, conceptual versus physically-based) but, to our knowledge, model identification in the face of data uncertainty remain largely unexplored. Given the presence of uncertainty in any hydrological modelling exercise, we believe that there is a need for developing guidelines to drive the selection of the most appropriate model depending on observation uncertainty and the actual information content of data.

We would like to provide here a first contribution on this issue and in particular we aim to inspect how data uncertainty propagates through a rainfall-runoff model depending on model complexity. In fact, we argue that the impact of measurement errors on parameter calibration and hydrological modelling strongly depends on the model structure and parameter estimation variance. In our opinion, model complexity should be made commensurate to the information content of data and not just to the extension of the data base as it is usually done. However, one may wonder how to pursue the above commensuration.

On the one hand, intuition suggests that simpler models, which are characterised by limited flexibility, are more robust. Therefore they would be preferred when data uncertainty is suspected to be relevant, because robust models are believed to be not unduly affected by outliers or other departures from model assumptions. On the other hand, the non-linear structure of hydrological models may propagate errors in a counterintuitive fashion.

To better investigate this issue, we performed a simple experiment, by referring to a tributary of the aforementioned Po River, the Secchia River (Italy). The Secchia River basin is characterised by a contributing area of 1214 km^2, basin concentration time of around 12 hours, main stream length of about 70 km, and mean annual precipitation between 700 mm and more than 1500 mm per year. Observation of mean areal hourly rainfall and temperature over the basin, as well as river flows at the closure of the mountain basin, were collected for the year 1972. Rainfall was measured by using 5 tipping bucket raingauges displaced over the basin area, mean areal evapotranspiration over the basin was estimated with the radiation method, while river flows were measured through the rating curve method.

We performed a numerical experiment by using a simple linear reservoir to mimic the rainfall-runoff transformation of the Secchia River. The model counts one parameter only, namely, the constant k [t] of the linear reservoir. The optimal value for k was identified by using the Genoud optimisation algorithm and resulted equal to 89.93 hours. The Nash efficiency of the model in calibration is 0.64, which is a satisfactory value for a simple model as the linear reservoir. To provide a term of comparison, we note that highly complex spatially distributed models that were calibrated by using the same data set provided Nash efficiency (in calibration) of 0.81 [20]. Figure 2, left panel, shows observed and simulated annual hydrographs.

Then, we corrupted the river flow observations by multiplying them by 1.25 and 0.75, therefore introducing a systematic ±25% error. If river flows are derived by means of a rating curve, as in this case, such error can be originated by a systematic under/overestimation of the rating curve [16]. Rainfall and evapotranspiration data were kept unchanged. Model calibration was repeated after data corruption, thus obtaining k values of 142.16 and 70.26 hours for the -25% and +25% river flow corruptions, respectively.

It is interesting to compare the model simulations obtained with the lower and upper values of the linear reservoir parameter, namely, $k_{-25\%}$ and $k_{+25\%}$. In particular, Figure 3 (left panel) shows the distribution of the mean percentage difference $(Q_{up}-Q_{low})/Q_{opt}\cdot 100$ with respect to Q_{opt}, where Q_{low} and Q_{up} correspond to $k_{-25\%}$ and $k_{+25\%}$, respectively, and Q_{opt} is the river flow simulated with the optimal parameter value. Representation was limited to $Q_{opt} > 10$ m^3/s to avoid instability for very low flows. Also, for the sake of clarity we averaged the obtained data points over each consecutive 20 values of Q_{opt}.

We repeated the same experiment by using a more complex model, namely, HYMOD. It is a 5-parameter conceptual rainfall-runoff model that was introduced by [21]. HYMOD consists of a relatively simple rainfall excess model that is connected with two series of linear reservoirs: three identical reservoirs for the quick response and a single reservoir for the slow response. Parameters are the maximum storage capacity in the catchment, C [L], the degree of spatial variability of the soil moisture capacity within the catchment, b [-], the factor distributing the flow between the two series of reservoirs, α [-], and the residence time of the linear quick and slow reservoirs, K_s [T] and K_l [T], respectively. Evapotranspiration is accounted for in the same way as for the linear reservoir.

Model calibration yielded a Nash efficiency of 0.71, which testifies an improved performance with respect to the linear reservoir, which was expected in view of the higher number of model parameters and thus higher flexibility. Figure 2 (right panel) shows the observed and simulated annual hydrographs.

The right panel of Figure 3 shows the results of the sensitivity analysis and allows a visual comparison of the robustness of the two models to data uncertainty. In order to better illustrate the results, let us note that a hypothetical model with unlimited flexibility would fit the river flows (in calibration) perfectly, no matter what is the perturbation that one introduced in the river

flows themselves. Therefore, such a model would give the maximum sensitivity to data uncertainty. In particular, for the perturbation we introduced here, the statistics $(Q_{up}-Q_{low})/Q_{opt}\cdot 100$ would result identically equal to 50. Conversely, a model with no flexibility would give the same output no matter of data uncertainty and therefore would provide a identically null value for the above statistics. It follows that, by intuition, one would expect a larger sensitivity for the HYMOD model which is more flexible than the linear reservoir in view of the higher number of parameters.

Figure 3 shows that this is not always the case and counterintuitive results are possible. In fact, by analysing Figure 3 one may observe that HYMOD resulted significantly less sensitive to data uncertainty than the linear reservoir model. This outcome can be explained by considering that the calibration procedure focuses on high flows, in view of the objective function that was used here (the Nash efficienty). Thus, the linear reservoir reacts to positive perturbations of the peaks by decreasing *k*, which induce a decrease of the low flows as well. This consideration explains the progress of the sensitivity in the left panel of Figure 3, from negative to positive values. On the other hand HYMOD, being more flexible, is closer to the situation one would expect from unlimited flexibility. Sensitivity becomes more stable, no matter the magnitude of the river flow, and converges to a value of about 30%, which is significantly lower than 50%. Hence, one notes that the observation error is smoothed by HYMOD.

Overall, in this case one notes that the increased flexibility brings to a situation characterised by lower sensitivity and therefore more stability with respect to data perturbation. Thus, a model with a more robust structure results more sensitive to observation errors.

It may be argued that the above result is not general, but conditioned on the case study we considered here. We are currently testing several models with increasing complexity applied to different case studies. Anyhow, these counterintuitive results indicate that the sensitivity of

hydrological models to observation uncertainty should be carefully examined to identify the optimal model complexity in the face of observation uncertainty, because the actual results may contradict intuition and common sense.

To inspect the sensitivity of the simulation to a different model structure, we made an additional experiment by assuming a random error instead of a systematic one. In particular, we corrupted river flow data by using a random outcome from a Gaussian probability distribution with mean 1 and standard deviation equal to 0.12 [11]. The HYMOD model was then calibrated by using the corrupted river flows and the exercise was repeated 10 times, therefore obtaining 10 different simulations (in calibration mode) for the 1972 hourly river flows. Then, at each time *t* we computed the statistics $(Q_{max}-Q_{min})/Q_{obs}$ where the maximum and minimum values were computed across the 10 simulations for each time step. Figure 4 shows the progress of the above statistic depending on Q_{obs}. In this case also, representation was limited to $Q_{obs} > 10$ m^3/s and the obtained data points were averaged over each consecutive 20 values of observed flow.

One can see that the sensitivity of the simulation to data perturbation is much less significant. In this case the results meet one's expectation based on intuition: a random error in river flow observations is less impacting than a systematic error. The above results highlight the relevant role played by model complexity and therefore model identification when observation uncertainty is significant.

4. Reducing observation uncertainty and its impact

4.1 Hydraulic approaches and remote sensing techniques

As mentioned above, uncertainty in river discharge data tend to be much more relevant when the stage-discharge rating curve is extrapolated beyond the measurement range used for its derivation. Some authors have proposed the use of hydraulic models to reduce the inaccuracies

due to the extrapolation of rating curves [22]. Indeed, [23] showed that the indirect observation of discharges beyond the measurement range should better rely on process based approaches (e.g. hydraulics), instead of traditional extrapolation methods based on analytical black-box relationships (e.g power functions). It should be noted that hydraulic modelling has become easier to implement because of the increasing availability of topographic data and model codes [24, 25]. Such studies may help to obtain more reliable stage-discharge relationships in the extrapolation zone. A possible operational strategy could be to use the stage-discharge measurements to calibrate a hydraulic model and then to use the model to extrapolate the rating curve [23]. A hydraulic approach can also potentially include roughness variations due to changes in the state of the vegetation, which can be a relevant factor of alteration of the rating curve [13].

However, it must be said that the uncertainty of the hydraulic model, which is calibrated using ordinary flow data and then used to simulate extremely high flow conditions, is often not negligible and therefore needs to be carefully evaluated. For instance, [19, 26, 27] have shown that the effective roughness coefficients may be different when evaluated for different flow conditions. It is then recommended to constrain the model uncertainty by using some direct observations during high water conditions. To this end, the current proliferation of remote sensing data [28] (which has led to a sudden shift from a data-sparse to a data-rich environment for hydraulic modelling of floods [24]) can be extremely valuable. From space, satellites carrying Synthetic Aperture Radar (SAR) sensors are particularly useful for monitoring large flood events. In fact, radar wavelengths, which can penetrate clouds and enable data acquisition during day and night, are reflected by smooth open water bodies, and hence mapping of water surfaces becomes relatively straightforward [28]. Some examples of current satellite missions featuring SAR sensors with high potential for floodplain studies are: ERS-2, RADARSAT,

ENVISAT, COSMO-SkyMed, and TerraSAR-X [29]. Thus, we can constrain the uncertainty of hydrodynamic models by using SAR derived flood extent maps and therefore get more reliable estimation of river flows corresponding to flood conditions.

4.2 Exploiting the information content of data

Observation errors reduce the information content of data, to the extent that a part of the data set may become "disinformative", accordingly to the terminology introduced by [6, 7]. Actually, observation errors are anomalies in the related time series, which in some cases can be easily identified, especially if they are locally occurring. For instance, [30, 31] dealt with outlier detection in hydrological data. However, in many cases it is indeed difficult to detect anomalies in hydrological observations. Modelling exercises can be an interesting opportunity to this end. In fact, the inability of a model to fit data sets (or portions of them) could be an indicator of the presence of anomalies. Hence, models can play an important role in exploiting the information content and identifying disinformative data sets. However, there is the risk that the model assumes a non behavioural structure in the attempt to fit anomalous behaviours of the data. Data filtering during model calibration might be a valuable opportunity to reduce the above risk.

In particular, we claim here that spectral calibration of hydrological models [32, 33] can be a useful solution to weigh out disinformative observations which are locally occurring. Basically, spectral calibration is performed by comparing the periodogram of observed and simulated time series. Actually, the observed record is decomposed in the sum of sine and cosine waves with different frequency and the amplitude of each wave is matched with the corresponding one computed on the simulated record. The parameter set which ensures the best match is finally retained. If all the frequencies are matched, then the calibration produces similar results as a least squares procedure. However, a proper selection of the frequencies to be matched allows one to

give more stress on short rather than long term properties of the observed record. When disinformative observations are suspected to be present at local scale, one would better decide to optimise the long term properties of the series only, being the short ones possibly affected by local errors. Therefore, spectral calibration can be classified as a "selective" calibration strategy, where focus on different frequencies of the spectrum can be obtained by simply changing a routine parameter.

We illustrate the above concepts by performing another numerical experiment by using the HYMOD model of the Secchia River basin (Section 3). Here, we corrupted the observed river flow series by introducing a systematic increase of 30% to the data collected after September 7, 1972 and greater than 50 m^3/s. This corruption is representative of a systematic error in the rating curve which occurs after an assigned time step and only affects river flows located above a certain threshold [16]. Then, we recalibrated HYMOD by fitting the corrupted series. Figure 5, left panel, reports a sketch of the progress of the relative error $(Q_c-Q_{nc})/Q_{nc}\cdot 100$ against Q_{nc}, where Q_c and Q_{nc} are the simulations obtained by calibrating with corrupted and uncorrupted data, respectively. Representation is limited to $Q_{nc} > 10$ m^3/s and data points were averaged over each consecutive 20 values. It can be seen that the calibration procedure is sensitive to the data corruption, which causes a general increase of the simulated river flows.

The calibration was then repeated by matching the periodograms as described in [32]. The Nash efficiency obtained by fitting the uncorrupted data is 0.67, which is comparable to the value of 0.71 that was obtained for the same model by maximising the Nash efficiency itself (see Section 3). While fitting the corrupted data, the higher 150 frequencies (over a total number of frequencies which is equal to the integer part of $(N-1)/2$, where N is the sample size of the observed data series) were not matched, in the attempt to focus on low frequencies only. It can be seen that the simulation is much less sensitive to data corruption in this case, with the only

exception of a few low flow events. This result proves the capability of spectral calibration to give more value on selected behaviours of the time series.

An alternative to explicitly account for rating curve uncertainty when calibrating rainfall-runoff models is the limits of acceptability approach suggested by [34] and used by [7, 35]. This type of approach does not attempt to fit an optimal model. Rather, all models providing acceptable simulations (within the limits of acceptability) are retained, therefore allowing one to obtain an ensemble of model simulations and therefore an estimate of simulation uncertainty. More details can be found in [35].

5. Concluding remarks

Data uncertainty is increasingly recognised to significantly affect hydrological modelling and, in particular, flood risk studies. However, its actual impact remains largely unexplored. This paper showed that both flood frequency analysis and flood hazard mapping can be seriously impacted by errors that are commonly affecting river flow observations. It is argued that we need to: i) devise advanced approaches for reducing observation uncertainty; and ii) perform hydrological model identification and calibration in the face of observation errors. For the former (i), we indicated that recent progresses in hydrodynamic modelling and remote sensing data can potentially open interesting perspectives to reduce the uncertainty in river flow data referred to flood conditions. For the latter (ii), we showed that an appropriate choice of model complexity and calibration procedure may help one to significantly reduce the impact of data uncertainty. Even though the analysis presented in this paper is limited, the outcomes of these experiments indicated that the best modelling option to follow should be identified by (merely) relying on common sense, intuition and/or expert knowledge. For instance, we found that more complex models can result more robust to observation uncertainty, which is a counterintuitive outcome.

We also showed that the impact of data uncertainty can be significantly reduced by selecting a proper modelling strategy. In particular, when data uncertainty is suspected to be significant we suggest performing sensitivity analysis for different model structures to identify the more robust solution, as well as using calibration strategies which focus on long term behaviours of the river flow process. To this end, spectral calibration seems to be an interesting opportunity.

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Tables

Table 1. Summary statistics of the seven storm events.

Event #	1	2	3	4	5	6	7	All
Sample size	9697	4379	4211	3539	3345	3331	1034	29536
Mean (mm/h)	3.89	0.50	0.38	1.14	3.03	2.74	2.70	2.29
Standard deviation (mm/h)	6.16	0.97	0.55	1.19	3.39	2.20	2.00	4.11
Skewness	4.84	9.23	5.01	2.07	3.95	1.47	0.52	6.54
Kurtosis	47.12	110.24	37.38	5.52	27.34	2.91	-0.59	91
Hurst Exponent	0.94	0.79	0.89	0.94	0.89	0.87	0.97	0.89

Figure captions

Figure 1. Impact of the uncertainty of hydrological data on flood mapping. Example of flood inundation modelling of the June 2008 event along the River Po between Boretto and Borgoforte (Italy). Left panel: flood extent map derived by neglecting the uncertainty in river discharge data (the map shows the inundated areas in grey; left panel). Right panel: uncertain flood extent map derived by considering the inaccuracy of river discharge observation (the map shows the 5th, 50th and 95th percentiles in a grey scale).

Figure 2. Simulations obtained in calibration mode, with the best parameter set, with the linear reservoir (left) and the HYMOD model (right).

Figure 3. Sensitivity of the linear reservoir (left) and HYMOD (right) models to systematic data uncertainty. Q_{up} and Q_{low} are simulations in calibration mode, obtained by fitting perturbed river flow data. Perturbation was obtained by multiplying the observation by 1.25 and 0.75, respectively. Q_{opt} is the simulation obtained by fitting unperturbed data.

Figure 4. Sensitivity of the HYMOD model to random data uncertainty. Q_{max} and Q_{min} are maximum and minimum values of 10 simulation in calibration mode, obtained by fitting perturbed river flow data. Perturbation was obtained by multiplying the observation by a random outcome from a Gaussian probability distribution with mean 1 and standard deviation equal to 0.12.

Figure 5. Sensitivity of the HYMOD model to local anomalies in the data. Calibration is performed by minimising the Nash-Sutcliffe efficiency (left) and by using a spectral calibration method which is performed by excluding the higher 150 frequencies (right). Q_c and Q_{nc} are the simulations obtained by calibrating with uncorrupted and corrupted data, respectively. Representation is limited to $Q_{nc} > 10$ m^3/s and data points were averaged over each consecutive 20 values.

Figure 1
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Figure 2

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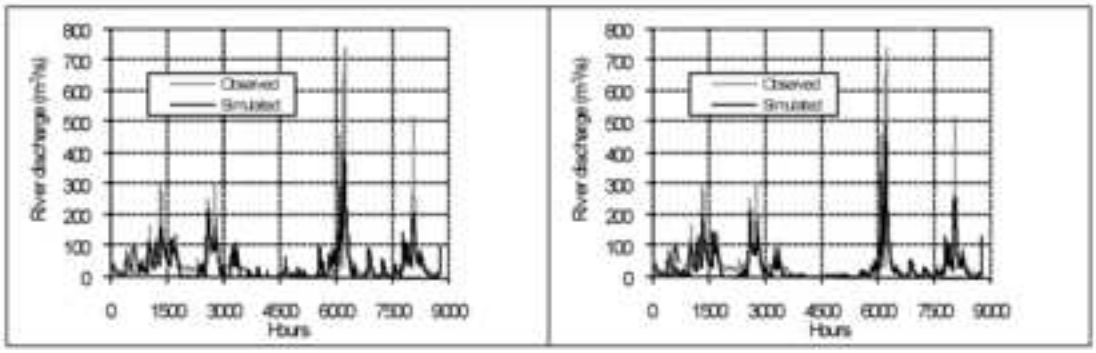

Figure 3

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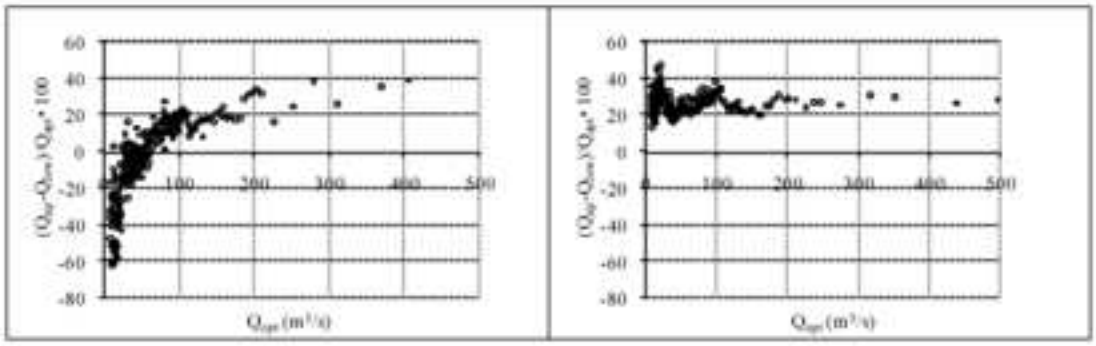

Figure 4

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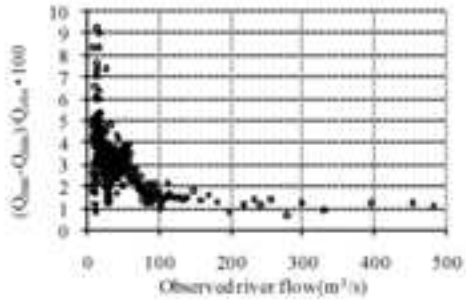

Figure 5

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