Impact of input data uncertainties on stormwater model parameters

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ABSTRACT
The use of urban drainage models requires careful calibration, where model parameters are selected in order to minimize the difference between measured and simulated results. It has been recognized that often more than one set of calibration parameters can achieve similar model accuracy. A probability distribution of model parameters should therefore be constructed to examine the model’s sensitivity to its parameters. With increasing complexity of models, it also becomes important to analyze the model parameter sensitivity while taking into account uncertainties in input and calibration data. In this study a Bayesian approach (including the Metropolis-algorithm) was used to develop a framework for quantification of impacts of uncertainties in the model inputs (i.e. systematic and random errors in rainfall time series) on the parameters of a simple integrated stormwater model. The model uses KAREN to simulate flow, and a very simple flow-based regression to calculate total suspended solids and total nitrogen loads. The framework was applied to two catchments in Australia. It was found that only systematic rainfall errors have a significant impact on flow model parameters. The most sensitive flow parameter was the effective impervious area, which interestingly can be calibrated to completely compensate for the input data uncertainties. On the other hand, the pollution model parameters were influenced by both systematic and random rainfall errors. It was also interesting that the parameters of both flow and water quality models behaved differently depending on circumstances (e.g. catchment type, data availability, data accuracy).

KEYWORDS
Urban drainage, Hydrological Model, Stormwater quality Model, Uncertainties, Monte Carlo Simulation, Metropolis algorithm.

INTRODUCTION
Urban drainage models are widely used for design, optimization and evaluation of sewer systems (Rauch \textit{et al.}, 2002). However, to obtain realistic modeling results, accurate calibration is a necessity. Model parameters have to be determined by manual or automatic calibration procedures, by comparing simulation data to observations. As shown in Gaume \textit{et al.} (1998), such calibration can lead to different parameter sets which all reach a similarly good fit between measured and simulated data. This can happen due to nonlinear criteria functions which may have local minima and result in a failure of the calibration process. Hence, certain calibration algorithms may not find the global minimum (Kanso \textit{et al.}, 2003), instead becoming ‘stuck’ in local minima. It is evident that these uncertainties increase - as well as the difficulty in analyzing them (Silberstein, 2006) – with increasing model complexity.
The behaviour of model parameters can be examined by applying a Bayesian approach (Markov-chain Monte Carlo Simulation). It has the advantage of not only getting one "best parameter set", but also a distribution of the most likely values of the model parameters (Mailhot et al., 1997; Kuczera and Parent, 1998; Kanso et al., 2003; Kuczera et al., 2006), that enables us to recognize ‘the most’ and ‘the least’ important calibration parameters of a model. Multiple minima of the objective functions can also be recognized.

There are a number of tools that can be used in the sensitivity analyses of model parameters. We adopted the software tool MICA (Doherty, 2003) that constructs the probability distribution function (PDF) of model parameters using the Markov chain Metropolis-Hastings approach (Doherty, 2003, Metropolis et al., 1953; Hastings, 1970). This approach has already been used to examine parameter sensitivity of stormwater models (e.g. Kanso et al, 2003).

However, model parameters are not the only source of uncertainties in our models. Input data uncertainties have been also recognized as key problem in accurate modeling. Hoppe H. and Gruening H. (2007) recently estimate that the influence of uncertainties in the input data already exceeds the effect of measures for optimization of sewer systems. Much work has been recently done on propagation of these uncertainties through models (e.g. Bertrand-Krajewski et al., 2003; Haydon and Deletic, submitted; Kavetski et al., 2006; Korving and Clemens, 2005; Kuczera et al., 2006; Lei, 1996; Rauch et al., 1998). However, all these studies were done on the already-calibrated models; ie. the models were first calibrated using the ‘best’ available data sets, and the impact of input data uncertainties were propagated through them while keeping the calibrated parameters fixed. This approach gives an incomplete picture of the effect of uncertainties in input data on the overall model calibration process.

Recently, a new framework was proposed that advocates that all sources of uncertainties should be propagated at the same time, since they can compensate for each other (Kuczera et al., 2006). This approach, known as the Total Error Framework, has only been tested on flow models in non-urban catchments. The methodology is rather complex, and is yet to be tested for water quality models or urban stormwater models.

The aim of our work was to develop a framework that will be able to effectively assess impacts of input data uncertainties (both random and systematic) on sensitivity of model parameters of an integrated stormwater flow and quality model. This work is a first step in development of the Total Error Framework for urban drainage models.

METHODS

The framework developed in this study is schematically represented in figure 1. The measured input data (i.e. rainfall) is transformed to account for possible random and systematic errors. These are used as inputs into MICA, together with the available measured data, to construct Probability Distribution Functions (PDFs) of the model parameters.
The Model
For flow modelling a simple linear reservoir model was chosen, as this approach is widely used in practice. The KAREN software package (Rauch and Kinzel, 2007) was adopted, due to its simple modular design. It is a continuous model that uses rainfall time series as inputs and then models flow rates. This model has four calibration parameters:

- effective impervious area \((EIA)\) \([m^2]\)
- concentration time \((T_C)\) \([sec]\)
- initial loss \((l_i)\) \([mm]\)
- evapotranspiration \((ev)\) \([mm/d]\)

The pollution load of TSS and TN was calculated using a very simple and commonly used relationship (e.g. it is used in SWMM (Rossman, 2007)):

\[
Load_i = W \cdot Q_i^b \cdot T
\]

where \(Load_i\) - pollution load per timestep \(i\), \(Q_i\)-flow (output from rainfall/runoff simulation), \(T\)- timestep, and \(W\) and \(b\) – two calibration parameters.

A time-step of six minutes was used for both flow and pollution modelling.

Data
The data used in this study are flow, rainfall and pollution measurements from two catchments in the inner eastern suburbs of Melbourne, Australia (Francey et al., submitted). Both catchments are drained by a separate sewer system, with measurements taken in a stormwater pipe.

Catchment 1 (Richmond) has a total area of 89.10 ha, land use is high-density residential with a total imperviousness of 0.74 and an average slope of less than 0.1%. Catchment 2 (Shepards Bush) has a total area of 37.98 ha, land use is medium-density residential with total imperviousness of 0.40 and an average slope of 4%. The two catchments were chosen to test the framework for catchments with very different land-uses, imperviousness and slopes.

For Richmond, two years of continuous rainfall and runoff measurements were available. Pollutographs of TSS and TN were available for 40 and 39 events, respectively (each pollutograph contained 10-20 discrete concentrations). For Shepards Bush, one year of continuous flow measurements, 32 events with TSS, and 19 events with TN measurements were available. The two water quality parameters, TSS and TN were selected for the analysis.
since they exhibit very different behaviour; TSS is particulate, while N is mainly dissolved (Taylor et al., 2005).

**Calibration**

The Nash-Sutcliffe efficiency coefficient \( E \) (Nash and Sutcliffe, 1970) was chosen as the objective function for comparing observed and predicted data points. Both models were calibrated initially using a generalized pattern search (GPS) algorithm in Matlab, in order to maximize \( E \). The flow model and the pollutant model are calibrated independently, which means that the flow input for the pollutant model comes from an already-calibrated flow model. Although this initial calibration is not compulsory for the further procedure (because a set of calibration parameters is gained during Monte Carlo simulation), it helps to estimate the possible range of calibration parameters.

**Uncertainty Analyses**

*Model parameter sensitivity*

To assess the uncertainties of model calibration parameters, a Bayesian Monte Carlo Simulation was undertaken using the software tool MICA (Doherty, 2003; Gallagher and Doherty, 2007), which is based on a Metropolis-Hastings Sampler (Metropolis et al., 1953; Hastings, 1970, Kuczera and Parent, 1998, and Kanso et al., 2003). As described above, flow and pollutant modelling were performed independently.

At the start, the flow calibration parameters (a parameter set) were randomly chosen using user-defined uniform distributions, the model was run, and the objective function calculated. Further sampling was then done from the normal distributions derived in an iterative way; the distribution parameters \( \mu \) and \( \sigma \) were ‘re-assessed continuously’ after each 20 iterations, by accepting only parameter sets that gave the objective function very close to its optima. In other words, the simulation results were compared to measured values for each timestep with the aim to minimize the the sum of squared differences between modeled and measured values (or maximise \( E \)). Seven Markov chains were simulated simultaneously, which means simulation starts from seven randomly chosen initial points. For each chain approximately 10,000 iterations were made. As the pollution model parameters are more sensitive than the flow model parameters, ten Markov chains with 10,000 iterations were used for pollutant modelling. The same procedure as for flow modelling was then applied.

Results from Markov chain Monte Carlo Simulation are PDFs of calibration parameters as well as the corresponding sum of squared differences which can be used to calculate \( E \).

**Impact of input data uncertainties on parameter sensitivity**

For both flow and pollution models, rainfall time series are the only inputs required. According to past studies (e.g. Butts et al., 2004; Carpenter and Georgakakos, 2004; Rauch et al., 1998; Yoo and Ha, 2002), the uncertainties in rainfall data are due to (a) systematic, and (b) random errors, that can be accounted for using the following approach:

\[
I_i^* = I_i(f + \varepsilon)
\]

where: \( I_i^* \) - rainfall intensity with the errors for timestep \( i \), \( I_i \) - measured rainfall intensity for timestep \( i \), \( f \)-fixed offset representing systematic error, and \( \varepsilon \) - random error sampled from a given uniform distribution.

For the systematic error an offset of ± 30% was chosen and the analysis was done for the three values of \( f \) (0.7, 1, and 1.3). At the same time the random error, \( \varepsilon \), was selected from a uniform distribution in the range [-0.5, 0.5]. This means that the analysis was performed for 6
combinations of systematic/random errors. Each combination was then used to construct PDFs of the model parameters by the means of MICA software tool.

Analysis of the results
In total, 2,700,000 model runs for both case studies and all types of input-data uncertainties were undertaken. The figures of PDFs were constructed for 4 flow parameters and 2 pollution model parameters, using a non-dimensional presentation. This means that the parameters are normalized within the range [0, 1] where 0 represents the minimum value and 1 represents the maximum value. Additionally, tables of all types of input data uncertainty analysis are presented where the parameters of the best fitting statistical standard distributions are shown. At the same time, E is reported for the all 6 combinations as well as E_{20%}, which is the mean E of the best 20% of the accepted simulation runs.

RESULTS AND DISCUSSION

Flow modelling
To compare the model parameters, the best fitting statistical standard distributions are evaluated using maximum likelihood estimation (Table 1). The normal distribution is characterized by the mean (μ), standard deviation (σ) and coefficient of variation (c_v = σ/μ, enabling us to compare distributions). The lognormal distribution is characterized by the mean (m) and variance (v). Table 1 also shows the best-obtained E and E_{20%}.

Table 1. The characteristics of the probability distribution functions of the flow model parameters (in bold are results for inputs with no errors, in italic are results for inputs with both random and systematic errors).

<table>
<thead>
<tr>
<th>systematic error σ</th>
<th>random error ε</th>
<th>Richmond 0.7 (-30%)</th>
<th>Shepards 0.5</th>
<th>Richmond 1.0</th>
<th>Shepards 0.5</th>
<th>Richmond 1.3 (+30%)</th>
<th>Shepards 0.5</th>
</tr>
</thead>
<tbody>
<tr>
<td>EIA [%]</td>
<td>normal dist</td>
<td>μ</td>
<td>49</td>
<td>48</td>
<td>37</td>
<td>32</td>
<td>35</td>
</tr>
<tr>
<td>σ</td>
<td>μ</td>
<td>6</td>
<td>6</td>
<td>6</td>
<td>14</td>
<td>16</td>
<td>4</td>
</tr>
<tr>
<td>c_v</td>
<td>μ</td>
<td>0.12</td>
<td>0.12</td>
<td>0.39</td>
<td>0.52</td>
<td>0.11</td>
<td>0.11</td>
</tr>
<tr>
<td>Tc [min]</td>
<td>normal dist</td>
<td>μ</td>
<td>49</td>
<td>50</td>
<td>51</td>
<td>69</td>
<td>49</td>
</tr>
<tr>
<td>σ</td>
<td>μ</td>
<td>8</td>
<td>9</td>
<td>9</td>
<td>31</td>
<td>42</td>
<td>8</td>
</tr>
<tr>
<td>c_v</td>
<td>μ</td>
<td>0.16</td>
<td>0.18</td>
<td>0.61</td>
<td>0.61</td>
<td>0.16</td>
<td>0.16</td>
</tr>
<tr>
<td>l_i [mm]</td>
<td></td>
<td>m</td>
<td>1.4</td>
<td>2.2</td>
<td>-</td>
<td>-</td>
<td>2.8</td>
</tr>
<tr>
<td>lognorm. d.</td>
<td></td>
<td>ν</td>
<td>3.2</td>
<td>17</td>
<td>-</td>
<td>-</td>
<td>3.7</td>
</tr>
<tr>
<td>e [mm/d]</td>
<td></td>
<td>uniform distributed</td>
<td>[0]</td>
<td>[0]</td>
<td>[0]</td>
<td>[0]</td>
<td>[0]</td>
</tr>
<tr>
<td>best E</td>
<td></td>
<td>0.75</td>
<td>0.75</td>
<td>0.61</td>
<td>0.59</td>
<td>0.75</td>
<td>0.75</td>
</tr>
<tr>
<td>mean E_{20%}</td>
<td></td>
<td>0.74</td>
<td>0.72</td>
<td>0.51</td>
<td>0.49</td>
<td>0.74</td>
<td>0.73</td>
</tr>
</tbody>
</table>

Model parameter sensitivity
The flow model KAREN was effectively calibrated for Richmond (E=0.75, Table 1), while for Shepard’s Bush it was less successful (E=0.61). For Richmond (Figure 2, top), the effective impervious area (EIA) and concentration time are normally distributed, the initial loss follows lognormal distribution, while the evaporation is uniformly distributed. The model is therefore sensitive to all parameters other than ev, which can take nearly any value from the specified range.

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The PDFs of the flow parameter are somewhat different for Shepard’s Bush. EIA is the only parameter which is really normally distributed, and therefore important for the model. It is clear that there are far more combinations of the parameters that can achieve similar ‘optimal’ objective function for this catchment than is the case for Richmond.

It is therefore clear that EIA is the most sensitive parameter, followed by concentration time ($T_C$). There are two possible explanations for the lack of identifiability in the case of Shepard’s Bush; either greater measurement errors (i.e. greater uncertainty in input data) or the model is less able to predict flow for catchments with low imperviousness, i.e. the model structure uncertainties are higher. The approach cannot discriminate between these 2 sources.

**Impact of input data uncertainties on parameter sensitivity**

It is clear that EIA is the only parameter that responded to systematic errors in input data in a significant way (Table 1). Its $\mu$ decreased with ascending rainfall intensity, while at the same time $\sigma$ decreased (figure 2 - left). However, impacts of random input errors are not highly noticeable, with Shepards Bush responding a bit more than Richmond to this disturbance.

It is interesting that $T_C$ - the second most sensitive model parameter for Richmond (Figure 2-top) - is not influenced by either systematic or random rainfall errors for this catchment (figure 2, right). However, for Shepards Bush, this parameter (although still not sensitive to systematic errors) is somewhat more sensitive to random errors.

Consequently, for both catchments, only systematic rainfall errors have a significant impact on the calibration process. Simulation results are not affected by random input-data errors.

**Figure 2.** Distribution of the flow parameters for Richmond (top) and Shepard’s Bush (bottom).
Most importantly, the results show that by calibrating the flow model parameters taking into account possible errors in the inputs, we can compensate (adjust the results) for these uncertainties.

**TSS modelling**

The characteristics of the PDFs of the TSS model parameters are given in Table 2 (as per those presented for flow in Table 1), while figure 3 shows the distribution of the calibration parameters $W$ (left) and $b$ (right) for the Richmond catchment. The generic lower Nash-Sutcliffe efficiency coefficient $E$ in the calibration of the pollution load model is expected, given that the model implicitly uses the flow model underneath, i.e. the actual uncertainty of the load model is added to the $E$ already exemplified in Table 1. It is clear that, for rainfall inputs without errors, $b$ is normally distributed and $W$ has two optimal peaks (although this can be reasonably approximated with the log-normal distribution for comparison).

Systematic error of rainfall input has no significant effect on the calibration parameters of the TSS model as those are balanced during flow calibration by $EIA$. On the other side random rainfall uncertainties have an impact on $W$ and $b$. The parameter $b$, which is highly influenced by the flow because of its exponential relationship decreases. This is compensated by an increase of $W$. At the same time $c_v$ increased due to random error, which can be interpreted as higher calibration uncertainties.

**Table 2.** The characteristics of the probability distribution functions of the TSS model parameters (in **bold** are results for inputs with no errors, in *italic* are results for inputs with both random and systematic errors).

<table>
<thead>
<tr>
<th></th>
<th>Richmond 0.7 (-30%)</th>
<th>Shepards</th>
<th>Richmond 1.0</th>
<th>Shepards</th>
<th>Richmond 1.3</th>
<th>Shepards</th>
</tr>
</thead>
<tbody>
<tr>
<td>$f$</td>
<td>0.5</td>
<td>0.5</td>
<td>0.5</td>
<td>0.5</td>
<td>0.5</td>
<td>0.5</td>
</tr>
<tr>
<td>$e$</td>
<td>0.04</td>
<td>0.05</td>
<td>0.15</td>
<td>0.08</td>
<td>0.15</td>
<td>0.07</td>
</tr>
<tr>
<td>$m$</td>
<td>0.02</td>
<td>0.001</td>
<td>0.06</td>
<td>0.02</td>
<td>0.005</td>
<td>0.004</td>
</tr>
<tr>
<td>$W$</td>
<td>1.32</td>
<td>0.97</td>
<td>0.91</td>
<td>1.32</td>
<td>0.94</td>
<td>0.98</td>
</tr>
<tr>
<td>$\mu$</td>
<td>0.12</td>
<td>0.12</td>
<td>0.19</td>
<td>0.19</td>
<td>0.15</td>
<td>0.14</td>
</tr>
<tr>
<td>$\sigma$</td>
<td>0.09</td>
<td>0.12</td>
<td>0.21</td>
<td>0.14</td>
<td>0.16</td>
<td>0.14</td>
</tr>
<tr>
<td>$c_v$</td>
<td>0.33</td>
<td>0.30</td>
<td>0.30</td>
<td>0.35</td>
<td>0.29</td>
<td>0.34</td>
</tr>
<tr>
<td><strong>best E</strong></td>
<td>0.45</td>
<td>0.53</td>
<td>0.33</td>
<td>0.45</td>
<td>0.55</td>
<td>0.34</td>
</tr>
<tr>
<td><strong>mean E_{20%}</strong></td>
<td>0.43</td>
<td>0.52</td>
<td>0.29</td>
<td>0.45</td>
<td>0.55</td>
<td>0.29</td>
</tr>
</tbody>
</table>

Figure 3. Distribution of $W$ (left) and $b$ (right) for TSS modelling, Richmond ($e=0$; $f=0.7$, $f=1.0$ and $f=1.3$).

The trends are the same for both catchments, but due to a poor calibration performance for the less impervious catchment (Table 2), the results for Shepards have to be interpreted carefully.
In this regard also, the change of $E$ due to input-data uncertainties is noted; while $E$ for Richmond increases when applying rainfall uncertainties, there is a drop of $E$ for Shepards.

It can be concluded, that for TSS modelling (in contrast to flow modelling), the impact of random rainfall errors outweighs the impact of systematic errors, and uncertainties in determining calibration parameters increase.

**TN modelling**

Again the parameter PDFs are described using either normal or log-normal parameters (Table 3). However, for some cases, the PDFs did not follow any of these two models and thus these results could not be expressed by $\mu$ and $\sigma$, but by a single value (of central tendency) instead.

For TN modelling the two catchments behave very differently from each other. Similar to the results for TSS, modelling random rainfall uncertainties results in a better fit of simulation data and measurement data for Richmond, while the (already low) $E$ for Shepards Bush drops even further. Furthermore, the distribution of calibration parameters for Shepards Bush fits to a log-normal distribution, while calibration parameters of Richmond fit to a normal distribution. It is possible that this is a result of the differing imperviousness between the two catchments. However, there is also a possibility that differences in the data availability or rainfall patterns could lead to these differences.

**Table 3.** The characteristics of the probability distribution functions of the TN model parameters (in **bold** are results for inputs with no errors, in *italic* are results for inputs with both random and systematic errors).

<table>
<thead>
<tr>
<th></th>
<th>Richmond</th>
<th>Shepards</th>
<th>Richmond</th>
<th>Shepards</th>
<th>Richmond</th>
<th>Shepards</th>
</tr>
</thead>
<tbody>
<tr>
<td>$f$</td>
<td>0.7</td>
<td>1.0</td>
<td>1.0</td>
<td>1.3 (+30%)</td>
<td>0.5</td>
<td>0.5</td>
</tr>
<tr>
<td>$\varepsilon$</td>
<td>0 0.5</td>
<td>0 0.5</td>
<td>0 0.5</td>
<td>0 0.5</td>
<td>0 0.5</td>
<td></td>
</tr>
<tr>
<td>$\mu$</td>
<td>0.002</td>
<td>0.02</td>
<td>0.002</td>
<td>0.03</td>
<td>0.002</td>
<td>0.03</td>
</tr>
<tr>
<td>$\sigma$</td>
<td>0.01</td>
<td>-</td>
<td>0.01</td>
<td>-</td>
<td>0.01</td>
<td>-</td>
</tr>
<tr>
<td>$\mu$</td>
<td>2.4E-31.1E-3</td>
<td>-</td>
<td>2.5E-31.1E-3</td>
<td>-</td>
<td>2.5E-31.1E-3</td>
<td>-</td>
</tr>
<tr>
<td>$\sigma$</td>
<td>1.3E-5.1E-6</td>
<td>-</td>
<td>1.4E-5.1E-6</td>
<td>-</td>
<td>1.2E-5.3E-6</td>
<td>-</td>
</tr>
<tr>
<td>$\mu$</td>
<td>1.05</td>
<td>0.65</td>
<td>1.05</td>
<td>0.64</td>
<td>1.19</td>
<td>0.63</td>
</tr>
<tr>
<td>$\sigma$</td>
<td>0.09</td>
<td>0.05</td>
<td>0.09</td>
<td>0.05</td>
<td>0.06</td>
<td>0.04</td>
</tr>
<tr>
<td>$\mu$</td>
<td>0.78</td>
<td>0.78</td>
<td>0.76</td>
<td>0.77</td>
<td>0.76</td>
<td>0.77</td>
</tr>
<tr>
<td>$\sigma$</td>
<td>0.05</td>
<td>0.05</td>
<td>0.04</td>
<td>0.04</td>
<td>0.04</td>
<td>0.04</td>
</tr>
</tbody>
</table>

| best E    | 0.45 0.54 | 0.36 0.25 | 0.46 0.55 | 0.38 0.26 | 0.46 0.57 | 0.39 0.27 |
| mean E$_{20\%}$ | 0.45 0.48 | 0.29 0.19 | 0.46 0.50 | 0.31 0.19 | 0.46 0.50 | 0.32 0.20 |

Figure 4 shows the distribution for Richmond of $W$ (left) and $b$ (right) exemplified for $f=1.3$. Here random rainfall uncertainties – similar as for TSS modelling – result in an increasing $W$ and a decreasing $b$. Furthermore, this completely changes the parameter distribution. Without random rainfall uncertainties, $W$ is a rather fixed value of 0.002, $b$ is normal distributed with a mean value of 1.19. When applying random rainfall uncertainties, $b$ does not fit to a normal distribution anymore and becomes a nearly fixed value of about 0.6. Therefore, not only do the parameters’ values change, but also their influence on model results.
Figure 4. Distribution of $W$ (left) and $b$ (right) for TN modelling, Richmond; $f=1.3$, $\varepsilon=0.5$.

This impact cannot be seen for Shepards. The impact of rainfall error on parameter sensitivity is much less and leads to a slight increase of $b$ and a drop of $W$. The distribution of calibration parameters does not change at all. Further studies are needed to analyze the behaviour of different types of catchments, in order to better understand the mechanisms for this behaviour.

CONCLUSIONS AND OUTLOOK

This study shows how the Metropolis algorithm can be adapted for evaluating sensitivity of calibration parameters of urban drainage models (here rainfall / runoff and stormwater quality). Such parameter sensitivity analysis takes into account all sources of modelling uncertainties and boundary conditions, such as availability of data, measurement uncertainties or different catchment characteristics, but it is not possible to distinguish between these different sources. Calibration parameters compensate all uncertainties, in order to achieve simulation results with the best possible fit to measurement data.

By applying errors on input data, the model’s behavior due to data uncertainties can be analyzed. Here again one has to keep in mind that measured input-data already contains uncertainties and the applied input-data uncertainties represent additional data uncertainties. To some extent, the two catchments analysed show similarities in sensitivity of calibration parameters and behaviour due to input-data errors. Only systematic rainfall data uncertainties have impact on rainfall/runoff modelling and they can be compensated completely by adapting $EIA$.

Both calibration parameters of the TSS pollution model analyzed are influenced by systematic rainfall-data uncertainties, as well as by random rainfall data uncertainties, but random errors outweigh the impact of systematic errors. Decreases in the parameter $b$, which is highly flow-dependent, are compensated by an increase of $W$.

On the other hand, there are also differences in the impact of input-data uncertainties on parameter sensitivity. While random rainfall uncertainties completely change parameter sensitivity of the TN model for one catchment, they have no significant effect on calibration parameters of the other catchment. It is possible that those differences originate in different catchment characteristics (e.g. land-use, size, extent and nature of imperviousness), different rainfall characteristics or different data conditions (i.e. data-availability, data-accuracy). Therefore further studies are necessary to evaluate impact of catchment characteristics, data-availability and data accuracy.
REFERENCES


