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Impacts of measured data uncertainty on urban stormwater models

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SUMMARY

Assessing uncertainties in models due to different sources of errors is crucial for advancing urban drainage modelling practice. This paper explores the impact of input and calibration data errors on the parameter sensitivity and predictive uncertainty by propagating these errors through an urban stormwater model (rainfall runoff model KAREN coupled with a build-up/wash-off water quality model). Error models were developed to disturb the measured input and calibration data to reflect common systematic and random uncertainties found in these types of datasets. A Bayesian approach was used for model sensitivity and uncertainty analysis. It was found that random errors in measured data had minor impact on the model performance and sensitivity. In general, systematic errors in input and calibration data impacted the parameter distributions (e.g. changed their shapes and location of peaks). In most of the systematic error scenarios (especially those where uncertainty in input and calibration data was represented using 'best-case' assumptions), the errors in measured data were fully compensated by the parameters. Parameters were unable to compensate in some of the scenarios where the systematic uncertainty in the input and calibration data were represented using extreme worst-case scenarios. As such, in these few worst case scenarios, the model's performance was reduced considerably.

1. Introduction and background

Stormwater models underpin the decision making process in urban water management, policies and regulations. Moreover, they are key tools for the quantification of urban discharges and also for the design of stormwater treatment technologies. Uncertainties, however, are intrinsic to all models and it is hypothesised that the level of accuracy of any model's output is often compromised if the different sources of errors are not considered during the modelling exercise. Therefore, assessing uncertainties in models due to different sources of errors is crucial for advancing urban drainage modelling practice. Typically, three sources of random and systematic uncertainties are identified: errors in the measured input and calibration data, and errors due to incomplete or biased model structure (Butts et al., 2004). While the uncertainty in the calibrated parameter values combines the different sources, the impact of calibration and uncertainty analysis methods, different objective functions and calibration data availability on the model sensitivity are also recognised (Mourad et al., 2005; Dotto et al., 2012; Kleidorfer et al., 2012).

As with most models, the calibration of urban drainage models rarely results in one unique parameter set, and instead many equally plausible parameter sets are obtained, which reduces the confidence in the models when they are used for prediction (Kuczera and Parent, 1998). The uncertainty related to the model calibration parameters and its impact on the model outputs has been extensively studied (e.g. Kanso et al., 2003; Feyen et al., 2007). Global sensitivity analysis methods have been applied to estimate the confidence intervals around the model's prediction while revealing the sensitivity of the model outputs to each parameter (e.g. Feyen et al., 2007; Yang et al., 2008). Many methodologies are available to conduct these uncertainty/sensitivity analyses, including informal Bayesian methods (e.g. GLUE by Beven and Binley (1992)) and formal Bayesian approaches (e.g. MICA by Doherty (2003) and DREAM by Vrugt et al. (2009)). Comparisons have been made between these methods in various research areas (e.g. Yang et al., 2008; Matott et al., 2009), including urban drainage modelling (Dotto et al., 2012). These comparisons suggest that modellers should choose the method which is most suitable for the system they are modelling (e.g. complexity of the model's structure including the number of parameters), their skill and knowledge level, the available information, and the purpose of their study.

Measured data such as rainfall, flow rates and pollutant concentrations are needed for the application of urban drainage models. While rainfall data is the main input for most urban drainage models, flow rates and pollution concentration data are required for model calibration and validation. These measured datasets have

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inherent uncertainty and it has been shown that this uncertainty increases the data requirements for model calibration (Mourad et al., 2005). The input data used in stormwater modelling could be highly uncertain. For example, the main sources of uncertainties in rainfall intensities, commonly measured using tipping bucket rain gauges, are related to both rainfall catching and counting errors (Molini et al., 2005b). While splashing losses were found to be only up to 2% and evaporation losses were up to 4%, the wind losses were found to be inversely proportional to the rain intensity and were up to 30% for rainfall intensities around 0.25 mm/h (Sevruk, 1982; Rauch et al., 1998; Einfalt et al., 2002). Battery, logger and computer clock failures are also significant source of errors in rainfall measurements. For example, time drifts are inherent to any battery controlling logging device and values around 0.07 min/day were reported by McCarthy (2008). The spatial variability of rainfall often is a large source of errors when point source measurement methods are used (such as tipping bucket gauges). To address this issue radar rainfall data can be used to estimate precipitation, but radar data is also subject of several assumptions that introduce a number of errors For example, Krajewski et al. (2010) also report differences of up to 30% by comparing radar and rain gauges for 20 investigated storm events.

While addressed in related fields (e.g. hydrologic models: Krzysztofowicz and Kelly, 2000; Haydon and Deletic, 2009), the impacts of input data uncertainties on urban drainage models are largely unknown. Only a few studies evaluated the propagation of input data uncertainties through urban drainage models (Rauch et al., 1998; Bertrand-Krajewski et al., 2003) and in all of them, the models were first calibrated assuming that measured inputs and outputs are without error, and the impacts of input data uncertainties were then propagated through the models, while keeping the model parameters fixed. Kleidorfer et al. (2009) developed this further by assessing the impact of input data uncertainties on model parameters and found that the parameters of both flow and pollution models were influenced by systematic errors in input data.

In addition, the techniques used to measure urban discharges and associated water quality parameters, that are needed for calibration of stormwater models, also contain error (Bertrand-Krajewski et al., 2003; Harmel et al., 2006; McCarthy et al., 2008). For example, uncertainties in stormwater flow data, commonly measured using velocity-area measurement method, range from 2% to 20% (Harmel et al., 2006). While these random errors can be estimated, uncertainties in flow measurements due to systematic errors (often related to the height measurement and inaccurate velocity calibration or incorrect probe set-up) were not explored (Harmel et al., 2006).

Errors in water quality data are far larger than for flows or rainfall. Sampling, storage and analytical/laboratory methods all have inherent errors which contribute to the uncertainty in the final sample's pollutant concentration (Harmel et al., 2006). While sampling errors, related to the position of the probe, are significant in total suspended solids (TSS) measurements, with values up to 33%, they are not significant for dissolved pollutants that do not settle (Harmel et al., 2006). Some dissolved pollutants are more impacted by storage uncertainties; values up to 49% were reported for total nitrogen (TN) even for samples which are kept iced and are analysed within 6 h (Kotlash and Chessman, 1998). Uncertainty related to the laboratory analysis was less explored, but values from −9.8% to 5.1% have been reported for TSS (Harmel et al., 2006). Although these uncertainties are acknowledged in the urban drainage field, the impact of them on stormwater models has not been explored.

In addition, the combined impact of input and calibration data on urban stormwater models is unknown. However, valuable information can be obtained from related studies on modelling of large natural catchments. For example, Renard et al. (2008) and Thyer et al. (2009) applied the Bayesian Total Error Analysis methodology (BATEA proposed by Kuczera et al. (2006)) to evaluate the uncertainties in hydrological models arising from model input, output and structural errors. The BATEA framework is based on hierarchical Bayesian models and is very comprehensive and transferable (Renard et al., 2008). However, it is rather difficult for application, since it requires a large number of extra calibration parameters (that are associated with modelling the errors), is computationally demanding, and requires a significant level of understanding of the tested model structure and the of the assumed error models (Renard et al., 2008).

In summary, the combined effect of input and calibration data uncertainty on the parameters and outputs of urban drainage models has not been explored. Recently, the International Working Group on Data and Models of the Joint Committee on Urban Drainage that works under IWA and IAHR proposed an overarching framework that could address this issue (Deletic et al., 2012). However, the framework has never been tested, lacking practical details on the methodology. This paper is the first attempt to test the proposed framework for assessing the impact of both input and calibration data errors on the parameter sensitivity and predictive uncertainty of an urban rainfall runoff and water quality model using a rich Melbourne dataset.

2. Methods

2.1. Adopted stormwater models

Rainfall runoff model. KAREN (Rauch and Kinzel, 2007) was selected for the study because of its simplicity and proven performance for urbanised catchments (Kleidorfer et al., 2009). KAREN is a linear reservoir model, which only requires the catchment area and a rainfall time series as inputs to generate a series of flows originating from impervious areas (A_i) only. A_i of the catchment is calculated from total area (A_{tot}) and the calibration parameter effective impervious fraction (*EIF*) as $A_i = EIF \cdot A_{tot}$. Runoff from impervious areas occurs after a rainfall threshold has been exceeded (calibration parameter *li*). Therefore, effective rainfall *he* is calculated from measured rainfall *hn* and *li* as $he_j = hn_j - li_j$. The initial loss is calculated continuously in each timestep *j* and fills during rainfall and is drained during dry weather by a permanent loss calibration parameter (*eV*) according to $l_{i,j} = l_{i,j-1} - eV$. Surface runoff volume is calculated using the linear time-area method, which is related to the unit hydrograph method (Sherman, 1932). At the beginning of a rainfall event, the effective impervious area is increased according to the flow time on the catchment surface until the whole catchment contributes to runoff after the catchment's time of concentration (calibration parameter *TOC*). Consequently the runoff Q_j is calculated from *he* and A_i for each timestep *j* of length Δt according to $Q_j = h_{e,1} \cdot A_{i,j} + h_{e,2} \cdot A_{i,j-1} + \cdots + h_{e,k} \cdot A_{i,j-k+1} = \sum_{k=1}^{K} h_{e,k} \cdot A_{i-k+1}$. The index *k* represents the rainfall index ranging from 1 to $K = \mathrm{TOC}/\Delta t$, A_{i-k+1} is the effective impervious area for the current timestep.

Water quality model. A very well researched and widely adopted build-up and wash-off model (initially proposed by Sartor and Boyd (1972) was used to model TSS concentrations in catchments discharges. It was selected because of its widespread use in practice; e.g. it is used in SWMM (USEPA, 2007). The original model was slightly modified and hence the key equations are presented in Table 1 (formatted for a 6 min timestep).

The main modification from the original is in the wash-off stage. The concentration of pollutants in the runoff within a timestep (*C* in mg/L) is a power function of the catchment runoff modelled with KAREN (*q* in mm/h) divided by the catchment runoff coefficient (*RC* – here assumed as the *EIF* calibrated with KAREN).