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ICUD-0437 Training the urban water engineers of the future – the challenge of stormwater TSS model

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Summary

Urban water engineers increasingly rely on advanced models and mathematical techniques to solve their tasks. However, several sources of uncertainty affecting these tools are often neglected in practice, undermining the robustness of the simulation results. The education of future engineers should thus include knowledge on tools to support good modelling practices. In this study, first-year MSc students applied dynamic models to simulate stormwater TSS pollutographs. The assignment was designed to expose students to typical issues in urban drainage modelling: lack of data, limitation of model structures, inter-event variability, and different performance evaluation criteria.

Keywords

teaching, accumulation/washoff, model uncertainty, calibration

Introduction

Urban water engineers are increasingly applying advanced mathematical models to better design and operate urban drainage infrastructure. These model applications include sizing of elements of the drainage networks, minimization of pluvial flooding impacts, Real Time Control (RTC) of drainage networks and integrated management of urban water systems (García et al., 2015; Hammond et al., 2015; Bach et al., 2014).

Robust applications of these models requires a comprehensive evaluation of the different sources of uncertainties that can affect the results. These sources of uncertainty have been widely identified, analysed and discussed in scientific literature (e.g. Deletic et al., 2012). The research activities carried out during the past decades led to a variety of advanced mathematical tools for e.g. parameter estimation and uncertainty quantification, which struggle to be widespread in practice (cf. the procedures presented in e.g.Refsgaard et al., 2005; Rieger et al., 2012). Teaching curricula should therefore introduce urban water engineers to these advanced mathematical techniques, enabling a robust application of models across in the urban drainage field.

This study presents the experience gained in a MSc course at DTU Environment (Denmark), where environmental engineering students were exposed to typical uncertainty sources faced by urban drainage modellers: measurement uncertainty, model structural uncertainty, parameter uncertainty, calibration uncertainty. The exercise aimed at improving the students' understanding of the advanced tool that will allow a robust application of modelling tools in their future professional career.

Material and Methods

The students' assignment

The introductory course 12104 "Modelling of Environmental Processes and Technologies" is a 10 ECTS MSc course on the first semester of the first year of DTU Environment's master in environmental engineering. The course aims at providing a basic modelling knowledge to all the environmental engineering students at DTU Environment. Being at the beginning of the MSc education (where almost 50% of the students come from other BSc education than DTU Environment), the students have different backgrounds and few are familiar with urban drainage systems. The course is structured to follow the different steps of the model development (as outlined in e.g. Jakeman et al., 2006; Carstensen et al., 1997). The last assignment of the course is dealing with sensitivity analysis, parameter estimation and uncertainty analysis, enabling the students to "*Integrate models with data and practice through parameter estimation, sensitivity and predictive modelling*" (as stated in the course learning objectives).

In this context, the students were asked to apply a dynamic stormwater quality model to simulate TSS measurements from the Chassieu catchment in Lyon (see a description of the data in Metadier and Bertrand-Krajewski, 2012). This specific environmental process has been chosen due to the limitation of the existing model structures (see e.g. Bonhomme and Petrucci, 2017) and the inherent uncertainty of the available measurements (Bertrand-Krajewski, 2007), challenging the students to understand the drawbacks of existing modelling tools.

A total of 63 students were enrolled in the 2016 edition of the 12104 course. The assignment was carried out in 4-people groups (for a total of 16 groups) over a total of three weeks in November 2016.

Data and models

Among the over 300 events recorded at Chassieu, a selection of 45 events was provided to the students: 30 for calibration and the remaining 15 for verification. Ten calibration events were selected due to their evident first flush phenomena (identified by an analysis of the M(V) curves, as defined in Métadier and Bertrand-Krajewski, 2012), while the remaining 35 events were randomly selected (i.e. they did not show evident first flush).

Four different model structures were provided to the students (one model structure for each group). The traditional accumulation/washoff model was used as reference state-of-the-art model:

(i) *Traditional Accumulation/Washoff model (Model #0).* This model is the traditional accumulation-washoff model, which has been applied (with small modifications) since the 1970s. The mass balance for the available TSS mass $M(t)$ [g] depends on the initial mass M_0 and the TSS removal process, which is proportional to the runoff $Q(t)$ [m^3/s]:

$$\frac{dM(t)}{dt} = -Q(t) \cdot k_{rem} M(t) \quad (1)$$

This model has two parameters: M_0, K_{rem}.

(ii) *Simple nonlinear-relationship between flow and TSS* (Model #1) This model assumes a nonlinear relationship between the runoff Q [m3/s] and the TSS concentration C_{TSS} [g/m3]:

$$C_{TSS}(t) = c_1 \cdot Q(t)^{c_2} \quad (2)$$

The model has two parameters: c_1 and c_2.

(iii) *accumulation washoff with additive term* (Model #2) This model expands the traditional accumulation-washoff model (eq. 1) with a term accounting for background TSS concentration $C_{TSS,back}$ [g/m3]:

$$C_{TSS}(t) = k_{rem}M(t) + C_{TSS,back} \tag{3}$$

This model has three parameters: M_0, K_{rem} and $C_{TSS,back}$.

(iv) *Modified accumulation washoff (*Model #3) This model, similarly to Model #2, modifies the traditional accumulation-washoff model by introducing a non-linear relationship between the removed TSS mass and the stormwater flow:

$$C_{TSS}(t) = \frac{M(t)}{c_1 Q(t)^{c_2} + c_3} + C_{TSS,back} \tag{4}$$

This model has five parameters: $C_{TSS,back}$, M_0, c_1, c_2, and c_3

(v) *Injection(s) of conceptual tracers with a base TSS contribution* (Model #4) The model assumes a number *p* of punctual TSS releases, spread across the catchment, where a TSS mass $injMass_p$ [g] is released at a distance $distPulse_p$ [m] from the monitored point. The TSS pollutograph for each *p-th* pulse is then calculated by using the formula for one-dimensional advection-dispersion transport in open channels at the catchment outlet:

$$C_{TSS,p}(t) = \frac{injMass_p}{\sqrt{4\pi D_p t}} exp\left(-\frac{\left(distPuls_p - ut\right)^2}{4 D_p t}\right) \tag{5}$$

The final concentration is obtained by summing the *p* pollutographs and by adding a background concentration. The model has 3*p*+1 parameters: $C_{TSS,back}$, $distPul_p$, $injMass_p$, D_p.

Tools for sensitivity analysis and parameter estimation

To provide a glance of the multiple choices that a modeller has to face in real-life application of modellers, the students were provided with different possibilities to complete their assignment.

Two methodologies for sensitivity analysis were provided (Saltelli and Annoni, 2010): a linear regression approach, and the elementary elements method. Parameter estimation was performed by either a simple gradient-based optimizer (available in the Matlab package) or by applying the DREAM algorithm (Vrugt et al., 2009). The students were free to choose any available objective functions among those listed in Bennett et al. (2013) and to either perform event-based or long-term calibrations.

Results and Discussion

Data availability

Measurements from sewer systems are generally difficult to obtain: access to the monitored system is limited, sensors are exposed to harsh conditions, and frequent failures limit the number of good quality data. Fig. 1 shows some example where TSS data are missing or affected by great noise. Compared to other assignments in the same course, where students previously worked with data from experiments from the controlled environment of a laboratory, TSS measurement represent a *rougher* picture of available data. The students thus experienced the contrast between the data requirement from the modeller (which needs *good quality* measurements) and the actual available measurements.

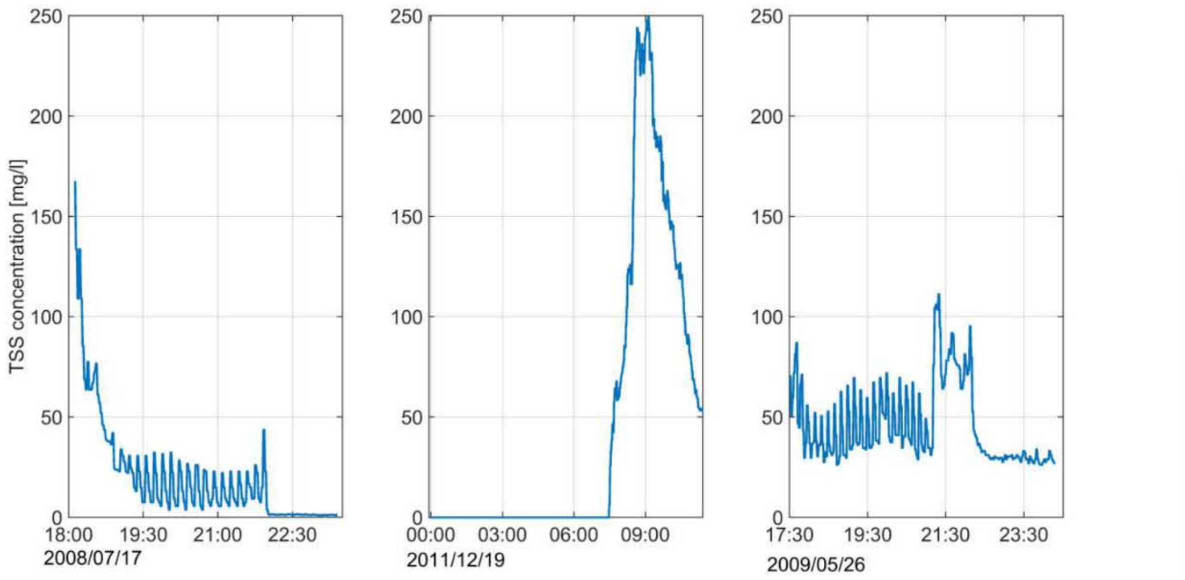

Fig. 1. *Example of TSS measurements for different events.*

Model structures

None of the five proposed model structures succeeded in satisfactorily simulating all the 45 events. An example from 6 events is shown in Fig. 2. Different events were better simulated by different model structures, showing the students how the proposed model structures could not account for all the processes driving TSS transport. This experience provided the students with a tangible example of the widely-known concept "*all models are wrong, but some are useful*" (intially introduced in Box, 1976). The students experienced that all models are based on simplified representations of reality, and therefore they may struggle in representing all the complexity of natural processes.

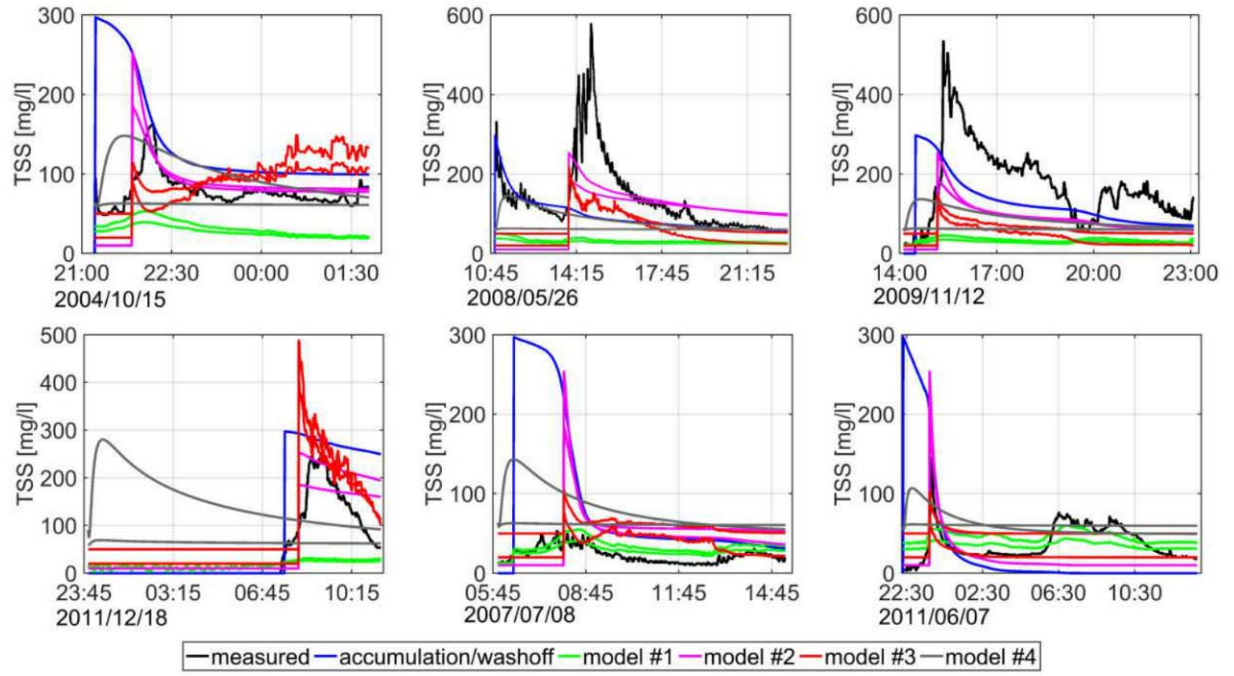

Fig. 2. *Comparison between measured (black) and simulated TSS concentration for different model structures (best parameter sets estimated 8 student groups) for 6 events.*

Tab. 1. *List of objective functions used by the students to evaluate model performance*

Name of the function	Equation (referred to Bennett et al., 2013)	Number of student group using the function
Mean Absolute Error (MAE)	4.6	2 (12.5%)*
Mean Square Error (MSE)	4.4	2 (12.5%
Nash-Sutcliffe model Efficiency (NSE)	6.1	2 (12.5%)
Root Mean Square Error (RMSE)	4.5	9 (56.3%)
RMSE - Standard deviation ratio (RSR)	6.8	1 (6.3%)

* One group calibrated the model against total cumulative TSS mass

Model parameters

The four test models have correlated or insensitive parameters, requiring a sensitivity analysis to simplify models before parameter estimation. Among the long list of possible objective functions (Bennett et al., 2013), the students utilized only five formulations (Tab. 1). The majority of the groups chose the Root Mean Square Error (RSME) to evaluate the model performance. Considering the limited modelling experience of the students (at the beginning of their MSc) education, this is not surprising. The RMSE is in fact commonly used as performance indicator in several courses throughout the BSc education and in the previous assignments of 12104, so it is a more familiar concept, compared to the vast opportunities listed in Bennett et al. (2013). Interestingly, one group focused on the purpose of modelling exercise: the estimation of stormwater pollutant loads. Based on this, the group calibrated the model against TSS loads instead of TSS concentrations, as all their colleagues did. The effect that the objective function has on the optimal parameter set is well described in literature, but this need to be underlined in the education of future urban drainage modellers

The majority of the student group (14 out of 16) chose the DREAM algorithm for parameter estimation, sometimes in the belief that a complex tools would be able to cope with complex processes. However, the optimal parameters estimated by DREAM provided unrealistic results when the model structure failed to fully represent the measurements. In some cases, the students uncritically utilized the parameters estimated by DREAM, even if they were outside their physical meaningful range. This was evident in the case of the additive term $C_{TSS,back}$ (model #2-#4), which was increased by the optimization algorithms in order to match the measured data, thereby compensating for the model structural deficiencies. The assignment resulted in 16 different optimal parameter sets: even groups using the same model structure and objective function provided different optimal parameter sets. This can be explained by the several subjective choices made during the assignment: choice of calibration parameters (based on the results of the sensitivity analysis), parameter ranges, number of iterations, etc.

These examples showed the students why modellers should always have a critical view on the model results, regardless of the complexity and the (supposedly satisfactory) reputation of the chosen tools. Also, there is not a single, objective, manner of calibrating a model, as several subjective choices are made by the modellers.

Conclusions

Future engineers will need mathematical models to better design and operate urban water systems. The presented experience focused on making the students confident with complex mathematical tools applied on environmental issues from the urban drainage field. By exposing the students to various challenges typical from urban drainage, a better understanding of the potential and limitation of the available tools was obtained, ensuring a better and more confident application of these tools. Concepts that are well established in the research community need to be included in the education programs, in order to ensure a more robust application of mathematical models. New questions also emerged to improve existing models for stormwater quality

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