Integrated urban drainage uncertainty assessment: the influence of the likelihood efficiency measures

Evaluation des incertitudes des modèles intégrés des systèmes d’assainissement calés en utilisant la méthode GLUE

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RESUME
L’analyse d’incertitude d’un modèle urbain intégré de drainage fait maison est présentée. Le modèle peut estimer à la fois les interactions entre le réseau d’égouts, le WWTP, le CSO et RWB et les modifications, en termes de qualité que les précipitations exceptionnelles urbaines causent aux masses d’eau réceptrices. L’incertitude a été établie au moyen de la méthodologie de GLUE qui se fonde sur une certaine hypothèse définie pour l’utilisateur ; une de ces dernières est l’adoption de l’équation de Nash-Sutcliffe pour l’évaluation des distributions de paramètre de probabilité. Afin de comprendre l’influence de l’équation d’efficacité, plusieurs expressions d’efficacité ont été considérées et l’incertitude correspondante a été évaluée. Le modèle a été appliqué à l’étude de cas de Savena (Bologna, IT) où la quantité et les données de qualité pendant la période de temps sec et pluvieux étaient disponibles. Les résultats sont intéressants et montrent fortement une influence de la méthodologie de GLUE par l’équation d’efficacité.

ABSTRACT
The uncertainty analysis of a home-made integrated urban drainage model is presented. The model is able to estimate both the interactions between sewers system, WWTP, CSO and RWB and the modifications, in terms of quality, that urban storm water causes inside the receiving water body. The uncertainty has been worked out by mean of the GLUE methodology which relies on some user-defined hypothesis; one of these is the adoption of the Nash-Sutcliffe equation to evaluate the likelihood parameter distributions. To understand the influence of the efficiency equation, several modelling efficiency expressions were considered and the correspondent uncertainty was evaluated. The model was applied to the Savena case study (Bologna, IT) where both quantity and quality data during dry and wet weather period were available. The results are interesting and show a strong influence of the GLUE methodology by the efficiency measure.

KEYWORDS
Environmental modelling, integrated urban drainage systems, uncertainty analysis, receiving water body, wastewater treatment plant.
1 INTRODUCTION

Although awareness was increasing about the quality processes of the storm water and the consequent preservation of the receiving water body (RWB), the urban drainage system has been frequently considered as divided into several subsystems: sewer system (SS), wastewater treatment plant (WWTP) and RWB neglecting any interaction. Today, the new trend to design as well as to manage the whole urban drainage system is the joint analysis of each compartment taking into account their mutually interactions.

Nowadays, even if several models are available to simulate single parts of the urban drainage system, only few of them can be adopted as reliable tools for an integrated water quality management. Therefore, one of the greatest challenges faced by researchers dealing with integrated modelling is the interconnection of these models and the definition of a full spectrum of modelling approaches that can suit the demands of specific applications (Rauch and Harremoës, 1996). However, due to a lack in the data for model calibration/validation, especially for quality modules, problems of uncertainty accumulation as well as uncertainty propagation throughout the different modules of the integrated model may occur (Willems, 2000).

Indeed, uncertainty analysis for integrated urban drainage modelling and, in general, for the quantity-quality models is relevant since there is a need to dispose a measure/index connected to the significance as well as reliability of the results obtained by a mathematical model. Furthermore, quantitative uncertainty analysis can provide an illuminating role to help target data gathering efforts (Frey, 1992). The evaluation of parameter uncertainties is necessary to estimate their impact on model performance (Beck, 1987). The purpose of quantitative uncertainty analysis is to use currently available information in order to quantify the degree of confidence in the existing data and models (Radwan et al., 2004).

2 ADOPTED MODELLING APPROACH

In this context, the uncertainty of an integrated home-made model previously developed has been assessed. The structure of the model will be briefly described remanding to Mannina et al. (2004) and Mannina (2005) for a more detailed description of the adopted algorithms. The model is able to estimate both the interactions between the different systems (SS, WWTP, CSO and RWB) and the modifications, in terms of quality, that urban storm water causes inside the RWB. Such a system is made up mainly of three modules:

- the rainfall-runoff and flow propagation sub-model, which is able to evaluate the quality - quantity features of SS outflows;
- the WWTP sub-model, which is representative of the treatment processes;
- the RWB sub-model, that simulates the pollutants transformations inside the water body.

Details about modelling approaches adopted in each sub-models are provided in previous literature (Mannina et al., 2004; Mannina, 2005; Freni et al., 2006; Mannina et al., 2006).

The model has been applied to an experimental catchment in Bologna (Italy) which consists of a part of the Bologna sewer network and a reach of the Savena river (Artina et al., 1999). Regarding the integrated model uncertainty assessment, by mean of the Generalised Likelihood Uncertainty Evaluation (GLUE) methodology has been carried out (Beven and Binley, 1992). According to such methodology the
problem of searching for an optimum parameter set is converted into a search for sets of parameter values that give reliable simulations. Furthermore, using Monte Carlo approach, simulations obtaining a likelihood score greater than a specified threshold (frequently zero) are considered "behavioural" with respect to a specific model output and they concur to the estimation of uncertainty bands. Following this approach there is no requirement to minimise (or maximise) any objective function, but information about the performance of different parameter sets can be derived from some index of goodness-of-fit (likelihood measure).

The present paper aims to study the formulation of likelihood efficiency measure and its influence on the modelling uncertainty response with respect to the different integrated modelling outputs (both considering quantity and quality variables). It has been demonstrated (Beven and Freer, 2001) that an erroneous selection of likelihood measure formulation can greatly affect both uncertainty analysis and further model calibration. In particular, in the present study, different likelihood efficiency measures have been used comparing the model uncertainty results according to the GLUE methodology.

3 METHODOLOGY

As discussed above, the efficiency measure effect on a home-made integrated urban drainage model has been performed by mean of the GLUE methodology (Beven and Binley, 1992). For the application of the GLUE methodology, the integrated model has been solicited by randomly picked parameter sets considering Monte Carlo Simulations. By mean of a likelihood measure, parameter sets are classified and sets with poor likelihood weights (with respect to a user-defined threshold) are discarded as "non-behavioural". All other sets from behavioural or acceptable simulation runs are retained and their likelihood weights are re-scaled so that their cumulative total sum is equal to 1. As likelihood measure, the Nash and Sutcliffe efficiency index (Nash and Sutcliffe, 1970) is generally employed. Once defined a likelihood index, the likelihood value associated with a set of parameter values may be treated as a fuzzy measure that reflects the degree of confidence of the modeller in that set of parameter values as a simulator of the system. The degree of confidence is derived from the model output coming from that set of parameter values. Therefore, treating the distribution of likelihood values as a probabilistic weighting function for the predicted variables allows an assessment of the uncertainty associated with the predictions, conditioned on the definition of the likelihood function, of the input data and model structure.

A method for deriving predictive uncertainty bounds using the likelihood weights from the behavioural simulations has been shown by Beven and Binley, 1992. The uncertainty bounds are calculated using the 5% and 95% percentiles of the predicted output likelihood weighted distribution. The uncertainty bounds should always contain the observations otherwise the model structure should be rejected. Wider bounds mean higher uncertainty in the estimation of the modelling output and thus lower confidence in the model results; vice versa, smaller bounds containing the observations are symptoms of reliable and robust modelling approaches.

It is evident that the GLUE approach is prone to some subjective decisions having a deep influence on the results of the uncertainty analysis. One source of subjectivity is the above mentioned selection of the likelihood efficiency measure that will be discussed in the following. One font of subjectivity arises from the definition of parameter variation ranges that can influence the analysis because it defines the domain where the model uncertainty is evaluated:
• the selection of small parameter variation ranges can show low uncertainty in the model output increasing the modelling level of confidence but, on the other hand, the sensitivity of the model to parameter variations can be fictiously reduced and the model can be more prone to be rejected because the observations have higher probabilities to fall outside the uncertainty bounds;
• the use of wide parameter variation ranges, on the contrary, gives more significant information of the influence of parameters on the modelling output but uncertainty bounds can widen dramatically reducing the modelling level of confidence.

The selection of the parameter variation ranges can be performed by considering the physical meaning of the parameters but this approach cannot be used for conceptual parameters having weak link to the physical system and it can produce too wide variation intervals leading to the above described problems. In order to avoid this font of subjectivity, parameter variation ranges can be estimated or by calibration on multiple events (Beven and Binley, 1992). In order to focus the study only on likelihood efficiency measure, this last approach has been used in the present study.

4 THE CASE STUDY
The integrated model and the uncertainty analysis have been applied to the catchment of the Savena river. The sewer system and the river studied in this work concern a part of the sewer network of Bologna, studied within the European Union research project INNOVATION 10340I (Artina et al., 1999).

The studied river reach is about 6 km length receiving 6 CSO discharge from the Bologna sewer network and 12 from the San Lazzaro sewer systems, a small centre in the surrounding area of Bologna. The CSOs generally operates also during small intensity rainfalls and often their discharge is of the same order of the river flow.

The sewer network is a part of the combined system serving the whole city of Bologna, which can be considered as hydraulically divided into many independent catchments, all connected to a WWTP. The part of Bologna connected to the studied river has an area of more than 450 ha, with an impervious percentage of about 66% and about 60,000 inhabitants.

During experimental survey, carried out within the INNOVATION European Research Project, from December 1997 to July 1999, about 50 events have been recorded, but, for only 5 of these, water quality aspects have been analyzed regarding both RWB and SS. The analyzed parameters were: BOD$_5$, NH$_4^+$, TSS, COD, pH, OD, temperature and conductivity. The variation range for each parameter has been obtained by the calibration of the 5 fully monitored events (Freni et al., 2006).

Here, only a part of the Savena river has been simulated (400 m in length downstream the most downstream CSO) because the contribution of this CSO to river pollution has been determined much more relevant respect all the others. The contribution of other polluting sources has been considered by monitoring river pollution load in the first cross-section upstream of the selected CSO and introducing this information as input in the models.

5 RESULTS ANALYSIS AND DISCUSSION
In the present study, the GLUE methodology has been applied different times varying the efficiency measure. More specifically, Table 1 shows the all equations employed in the present study. Several exponent values ranging from 1 up to 30 have been analysed in order to detect the influence of the efficiency measure as well as the effects of the information level increment onto the model. Indeed, the increment of the
exponent $N$ is analogous, from the mathematical point of view, to an extension of the data set dimension adopted for the uncertainty analysis. As a matter of the fact, the insensitivity to this coefficient can be interpreted as a model that is not able to “learn” from data (Mantovan and Todini, 2006). This behaviour is typical of the efficiency measures that do not depend directly on the number of data i.e. equation 1 and 2. Those uncertainty measures, in fact, averaging the error variance over the measured data variance, are less sensitive to the data set dimension.

Since WWTP outflow is not located in the analysed river reach, it has not been simulated; consequently, the WWTP sub-model of the simplified home-made model has been neglected. For running the GLUE analysis, a uniform prior knowledge distribution has been considered for all the parameters whose ranges (Freni et al., 2006) have been selected considering the calibrated values obtained for all the 5 available events (Beven and Binley, 1992). Each run of the GLUE methodology has been based on 1,000 Monte Carlo behavioural simulations. The number of simulations performed for each GLUE application has been estimated by a preliminary analysis (Freni et al., 2006) where the number of simulations against the model output has been detected in order to evaluate the consistency of the sample with respect to uncertainty evaluation.

<table>
<thead>
<tr>
<th>Description</th>
<th>Adopted equations</th>
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<tbody>
<tr>
<td>Based on Nash and Sutcliffe efficiency criterion with shaping factor $N$ (Freer et al., 1996)</td>
<td>$E = \left(1 - \frac{\sigma_e^2}{\sigma_0^2}\right)^N$ (1)</td>
</tr>
<tr>
<td>Based on exponential transformation of error variance and measured data with shaping factor $N$ (Freer et al., 1996)</td>
<td>$E = \exp\left[-N\frac{\sigma_e^2}{\sigma_0^2}\right]$ (2)</td>
</tr>
<tr>
<td>Based on exponential transformation of error variance with shaping factor $N$ (Freer et al., 1996)</td>
<td>$E = \exp\left[-N\sigma_e^2\right]$ (3)</td>
</tr>
<tr>
<td>Based on inverse error variance with shaping factor $N$ (Beven and Binley, 1992)</td>
<td>$E = \left(\sigma_e^2\right)^{-N}$ (4)</td>
</tr>
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Table 1. Likelyhood efficiency measures adopted; $\sigma_e^2$ is the error variance; $\sigma_0^2$ is the variance of the observations

In order to detect the effect of the acceptability measure, the model outputs against the exponent values, $N$, for the four efficiency equations (table 1), have been considered. The model response has been evaluated in terms of maximum flow rate and hydrograph flow volume, for the quantity aspects, whereas, maximum BOD ($\text{BOD}_{\text{max}}$), BOD load and maximum oxygen depletion ($\text{OD}_{\text{max}}$) for the quality ones.

In Figure 1 the main integrated urban drainage model outputs against different values of $N$ have been reported for the efficiency criterion according to Nash-Sutcliffe. Analysing the figures the following considerations can be pointed out:

- the uncertainty bounds width, i.e. the difference between the upper and the lower bands, are wider for the quality modules (Fig. 1c-1e) than for quantity ones (Fig. 1a and 1b);
- the increment of the $N$ value has an effect of accentuating the weight given to the better simulation and such aspect leads to get a thinner uncertainty bands increasing the $N$ value;
- for $N$ values higher than 10 there is no variation of the uncertainty bands hence the model becomes insensitive to the efficiency measure;
- even if the uncertainty bound gets smaller increasing the value of exponent $N$, the maximum efficiency simulation is always inside it ensuring the operator about the acceptability of modelling hypothesis;
this aspect is relevant because different results would generate doubts on the applicability of GLUE methodology for verifying the applicability of a modelling approach.

Figure 2 shows the model results in the RWB for the efficiency measures 2, 3 and 4 in terms of $Q_{\text{max}}$ for the quantity module, and BOD$_{\text{max}}$ for the quality one; analogous considerations can be drawn for the other model outputs. Comparing the Figures 2c and 2d as well as 2e and 2f, respectively, for the quantity and for the quality aspects, a reduction of the uncertainty band width can be observed. Such results, since it is valid for the efficiency measures that are independent of the measures variance, can be seen as the model incapability to “learn” from the data. Indeed, for such measures, the increasing of the N values is analogous to an increment of the data set dimension, as discussed above. On the other hand, the efficiency measure 4, shows a good ability to fit the measured data and it can be observed that also for low values of N, leads to get a strongly reduction of the uncertainty. However it has to be stressed such reduction uncertainty is a mathematical reduction due to the effect of the exponent N and it has to be interpreted as correspondent to the effect of an increment of data sets measured.

Globally comparing all the efficiency measures some considerations may be drawn also considering the analogy described between the increment of measured data set dimension and the values of exponent N:

- Nash-Sutcliffe index has the relevant defect of not being able to “learn” from data set increments thus not suggesting its use in the cases where the extension of measure campaign is expected.
• The use of exponential criteria, even if still dependent on measured data variance, partially solve the problem and results in a better ability of learning from data by the model.

• A specific comment should be provided for equation 3 because this exponential criterion seems to be more efficient on quantity variables than on quality variables; this behaviour can be explained by the higher error variance that characterises quality variables modelling and by the absence of an averaging function given, in equation 2, by the measured data variance; willing to assess a general consideration, equation 3 should be used in cases where error variance is expected to be low otherwise a more conservative equation 2 should be used.

• Equation 4 does not have the same problems of equation 3 probably because error variance is not inserted in an exponential expression; the equation demonstrated a good sensibility to data set extension and, in cases where few data are available, it guarantees uncertainty bounds similar to other criteria.

Figure 2 RWB model outputs adopting efficiency measures 2, 3 and 4, respectively, a-b, c-d and e-f, for different N values

CONCLUSIONS
The uncertainty analysis of a home-made integrated urban drainage model has been carried out by mean of the GLUE methodology. The study was aimed to the
evaluation of the influence of the efficiency measure on the uncertainty bound and on the operator confidence in model applicability. The need of such study relies in the consideration that the GLUE methodology relies on some subjective hypotheses that prevent its objective application. One of them includes the functional form of the efficiency measure to determine whether a specific parameters set is behavioural. The results confirm such influence obtaining in the field of integrated urban drainage modelling results similar to those previously obtained by Freer et al. (1996) in the hydrology field. The results pose doubts about the effectiveness of GLUE for the evaluation of the model uncertainty because its objective evaluation is not possible and, apparently, the model seems to gain scarce advantage from the extension of available measure dataset. This behaviour can be solved by a wise selection of the efficiency measure even if it should be based on careful analysis of the measured data variance and on their availability.

Despite the arbitrariness and non-objective elements in GLUE, its application has been informative for an insight into the model sensitivity to parameter variation, for insight into parameter interdependence and for providing estimates of parameter-induced uncertainty in a field of science usually devoid of uncertainty quantification.

LIST OF REFERENCES


