# Receiving water quality assessment: comparison between simplified and detailed integrated urban modelling approaches

Giorgio Mannina and Gaspare Viviani

## ABSTRACT

Urban water quality management often requires use of numerical models allowing the evaluation of the cause–effect relationship between the input(s) (i.e. rainfall, pollutant concentrations on catchment surface and in sewer system) and the resulting water quality response.

The conventional approach to the system (i.e. sewer system, wastewater treatment plant and receiving water body), considering each component separately, does not enable optimisation of the whole system. However, recent gains in understanding and modelling make it possible to represent the system as a whole and optimise its overall performance. Indeed, integrated urban drainage modelling is of growing interest for tools to cope with Water Framework Directive requirements. Two different approaches can be employed for modelling the whole urban drainage system: detailed and simplified. Each has its advantages and disadvantages. Specifically, detailed approaches can offer a higher level of reliability in the model results, but can be very time consuming from the computational point of view. Simplified approaches are faster but may lead to greater model uncertainty due to an over-simplification. To gain insight into the above problem, two different modelling approaches have been compared with respect to their uncertainty. The first urban drainage integrated model approach uses the Saint-Venant equations and the 1D advection-dispersion equations, for the quantity and for the quality aspects, respectively. The second model approach consists of the simplified reservoir model. The analysis used a parsimonious bespoke model developed in previous studies. For the uncertainty analysis, the Generalised Likelihood Uncertainty Estimation (GLUE) procedure was used. Model reliability was evaluated on the basis of capacity of globally limiting the uncertainty. Both models have a good capability to fit the experimental data, suggesting that all adopted approaches are equivalent both for quantity and quality. The detailed model approach is more robust and presents less uncertainty in terms of uncertainty bands. On the other hand, the simplified river water quality model approach shows higher uncertainty and may be unsuitable for receiving water body quality assessment.

**Key words** | mathematical modelling, river water quality, sensitivity analysis, uncertainty analysis, urban drainage integrated modelling

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## INTRODUCTION

The increasing sensitivity towards water quality environmental issues led to the setting up of water quality integrated approaches and the definition of water quality criteria that better represent the receiving water body quality status (Mannina *et al.* 2008). More specifically, compared to the past, the tendency today is to design and

doi: 10.2166/wst.2010.404

manage the whole integrated urban drainage system, i.e. Sewer System (SS), Wastewater Treatment Plant (WWTP) and Receiving Water Body (RWB), considering each component not separately but jointly (Harremoës & Rauch 1996; Rauch & Harremoes 1996; Erbe *et al.* 2002; Rauch *et al.* 2002; Butler & Schütze 2005; Erbe & Schütze 2005; Freni *et al.* 2009*a*,*b*, 2010). This integrated approach is implicitly present in the Water Framework Directive (WFD) that introduces the stream-standard approach to river water quality analysis in contrast to the old emission-standard, and it enhances the importance of integrated design and management of urban drainage systems (European Union 2000*a*,*b*; Chave 2001). The goal set in the directive is to reach a good ecological status of all water bodies throughout the catchment, rather than prescribing certain design rules specific to individual areas.

In order to put the integrated planning approach into practice, the engineer requires modelling tools for his work that allow him to rebuild the cause–effect relationship between the input(s) (i.e. rainfall, pollutant concentrations on catchment surface and in sewer system) and the resulting water quality response. Today, several models are available to simulate single parts of the urban drainage system, but only a few of them can be adopted as reliable tools for 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.

Two different kinds of approaches are more often adopted: physically based detailed models and simplified conceptual models. Physically based models simulate the system by using algorithms whose parameters have a clear physical meaning representing a specific characteristic of the simulated system (Freni *et al.* 2008*a*; Mannina & Viviani 2010*a*). Conceptual models use simplified algorithms and their parameters do not necessarily have correlation with the real simulated systems (Vaes & Berlamont 1999; Willems 2006; Willems 2010). As a consequence of this simplification, different physical–chemical phenomena that take place during the pollution generation and its propagation are considered in an aggregated way. A simplified approach focuses on a reduced number of processes for which reliable information is more frequently available but, on the other hand, the process parameters are more site specific and models need strong calibration. However, these latter models show the advantage of shorter calculation time, which may constitute an incentive when long-term simulation is necessary and also whenever a measure of the reliability of the model results is needed (i.e. uncertainty analysis). Indeed, especially for detailed models the whole computational time of the integrated model may be prohibitive for carrying out long-term simulations of the whole system as well as whenever a large number of repeated simulations are needed (i.e. uncertainty analysis). More specifically, the weak point from the computational point of view is the hydraulic equations, which describe flow propagation in sewer pipes and rivers, i.e. the Saint-Venant Equations (Meirlaen *et al.* 2001, 2002). Indeed, due to the fact that such equations are non-linear partial differential equations, the solutions are often time consuming, requiring complex numerical algorithms to solve, thus difficult to use for optimisation studies. To cope with such a problem, Meirlaen *et al.* (2002) suggested use of simplified models such as reservoir models that are characterised by reduced computational time compared to detailed ones. Recently, Willems (2010) proposed the use of parsimonious models (i.e. model structure with very limited number of processes and parameters) in order to cope with the long computational time of detailed models. Although the results for the presented model application were satisfactory, Willems (2010) concluded that a comparison with more detailed overparameterised water quality models would be useful to assess in a quantitative way the advantages and disadvantages of both types of models.

In case of a too simplified model approach, an increase of the integrated model uncertainty may arise due to an over-simplification of the model approach. Uncertainty of a model is stated by giving a range (or band) of values that are likely to embrace the true value of a specific simulated variable: stricter uncertainty bands demonstrate lower uncertainty, while larger bands are caused by highly uncertain models. Using the concept of uncertainty, the best model is the one able to correctly simulate a specific variable minimising the width of uncertainty bands. Three main uncertainty sources are generally classified: uncertainty of the model input variables (input uncertainty), uncertainty of the model parameter values (parameter uncertainty) and uncertainty originating from the imperfect description of the physical reality by a limited number of mathematical relations (model structure uncertainty).

Uncertainty analysis for integrated urban-drainage modelling, and for quantity–quality models in general, is relevant because there is the need to dispose a measure/index connected to the significance and reliability of the results obtained by a mathematical model. Indeed, despite the important role played by such tools, they can be very imprecise. This circumstance is mainly due to limited amount of water quality sampling data (Willems 2008; Mannina & Viviani 2009, 2010*a*). Indeed, the water quality gathering campaigns are extensive and generally require large economic as well as human resources that are not always available. In addition, information about model boundary conditions, such as sources of pollution, often suffer from the same shortcomings, especially for distributed variables, which are difficult to measure (pollution runoff, sediment quality, etc.). In summary, lack of data to support model identification is a major cause of model uncertainty (McIntyre *et al.* 2003). Therefore, uncertainty analysis must be performed for integrated urban water quality models in order to be able to quantify the level of reliability of the model results and hence the level of safety in the case of model employment for risk analysis. Uncertainty quantification enables us to use currently available information to quantify the degree of confidence in the existing data and models (Willems 2008). Quantitative uncertainty analysis can provide an illuminating role for problems where data are limited and where simplifying assumptions have been used in order to help identify the robustness of the conclusions and to help target data-gathering efforts (Frey 1992).

The fundamental importance of uncertainty in water-resource management is also illustrated by the EU Water Framework Directive that includes the precautionary principle (European Union 2000*a*,*b*). This latter aims to protect humans and the environment against uncertain risks and it cannot be applied without the inclusion of uncertainty assessments into the decision-making process (Refsgaard *et al.* 2007). The purpose of quantitative uncertainty analysis is thus the use of currently available information in order to quantify the degree of confidence in the existing data and models (Radwan *et al.* 2004). Furthermore, uncertainty analysis can play an illuminating role in helping to target data-gathering efforts (Frey 1992; Bertrand-Krajewski 2007). The evaluation of parameter uncertainties is necessary to estimate their impact on model performance and for their calibration (Beck 1987).

In contrast to other research fields such as hydrology, and despite the important role played by uncertainty, to date only a few studies have been reported throughout the technical literature for river water quality models (among others, McIntyre *et al.* 2003; Marsili-Libelli & Giusti 2008). Indeed, as pointed out by McIntyre *et al.* (2003), uncertainty identification in many contemporary models, such as WASP5 (Ambrose *et al.* 1993), MIKE11 (Havnø *et al.* 1995) and CE-QUAL (Cole & Wells 2000), is difficult because they are relatively complex and often linked to computationally intensive hydrodynamic, among other, modules.

Uncertainty analyses usually focus on uncertainties in model parameters and predictions within one specified model structure (Jia & Culver 2008). Modelling overall uncertainty is then adopted as a measure of operator confidence in the model being representative of reality.

Integrated urban-drainage models are complex as they involve several parameters that must be calibrated for a correct model application. Furthermore, due to the fact that integrated approaches are basically a cascade of sub-models (simulating SS, WWTP and RWB), uncertainty produced in one sub-model propagates to the following ones depending on the model structure, the estimation of parameters and the availability and uncertainty of measurements in the different parts of the system. Uncertainty basically propagates throughout a chain of models in which simulation output from upstream models is transferred to the downstream ones as input. The overall uncertainty can differ from the simple sum of uncertainties generated in each sub-model, depending on well-known uncertainty accumulation problems (Willems 2008).

Concerning the balance between sensitivity and model complexity, recently Lindenschmidt (2006) computed the error and the sensitivity for the river water quality modelling considering different complexities, and confirmed the hypothesis formulated by Snowling & Kramer (2001) stating that, as a model becomes more complex in terms of increased number of parameters and variables, the error between simulations and measurements decreases and the overall model sensitivity increases. The aforementioned hypothesis has been tested using several types of models: river water quality (Lindenschmidt 2006), transport in groundwater (Snowling & Kramer 2001) and heavy metal transport in lotic waters of different scale (Lindenschmidt & Hesse 2005).

In order to gain insights into the above problem, two different river water quality modelling approaches for the simulation of the RWB have been compared with respect to their uncertainty.

The two approaches, addressed in the following as detailed and simplified river water quality modelling approach, respectively, Detailed River Water Quality (DRWQ) and Simplified River Water Quality (SRWQ), have been incorporated in an integrated bespoke urban drainage model developed in previous studies (Mannina 2005). However, the difference between simplified and detailed integrated urban modelling approaches in this study only lies in the river water quality model (as all other sub-models, e.g. rainfall/runoff, SS, WWTP, are the same). The DRWQ approach is based on the Saint-Venant equations for the quantity aspects and on the advection–dispersion equations for the quality ones. On the other hand, SRWQ approach is based on the reservoir modelling concept both for the quantity and for the quality aspects. For the uncertainty analysis, the Generalised Likelihood Uncertainty Estimation (GLUE) procedure proposed by Beven & Binley (1992) has been employed. The GLUE procedure requires a large number of Monte Carlo simulations where the random sampling of individual parameters from probability distributions is used to determine a set of parameter values. Following this approach, model reliability was evaluated on the basis of their capacity of globally reducing the uncertainty (Beven & Binley 1992). The models have been applied to an experimental catchment in Bologna (Italy) where quantity and quality data were available.

## THE URBAN DRAINAGE INTEGRATED MODEL

In the present study, as discussed in the introduction, two river water quality modelling approaches for simulating RWB behaviour have been compared with different complexity levels. Those approaches have been incorporated in an integrated bespoke urban drainage model developed in previous studies (Mannina 2005; Mannina & Viviani 2010*a*). For the sake of conciseness, only the model structure will be discussed next, referring to earlier publications of the authors for further details (Mannina *et al.* 2004; Mannina 2005). The model is able to estimate both the interactions between the different systems (SS, WWTP and RWB) and the modifications, in terms of quality, that urban stormwater causes inside the RWB. Such an integrated SS–WWTP–RWB system is made up mainly of three sub-models (Figure 1):

- the rainfall–runoff and flow propagation sub-model, which is able to evaluate the quality–quantity features of SS outflows and simulates ancillary structures such as Combined Sewer Overflow (CSO) device and storm water tanks (SWT);
- the WWTP sub-model, which is representative of the treatment processes;
- the RWB sub-model that simulates the pollution transformations inside the river.

The first sub-model, reproducing the physical phenomena which take place both in the catchments and in the sewers, allows determination of the hydrographs and pollutographs in the sewers. This sub-model is divided into two connected parts: a hydrological–hydraulic module, which calculates the hydrographs at the inlet and at the outlet of the sewer system, and a water quality module, which calculates the pollutographs at the outlet for three pollutants (TSS, BOD and COD).

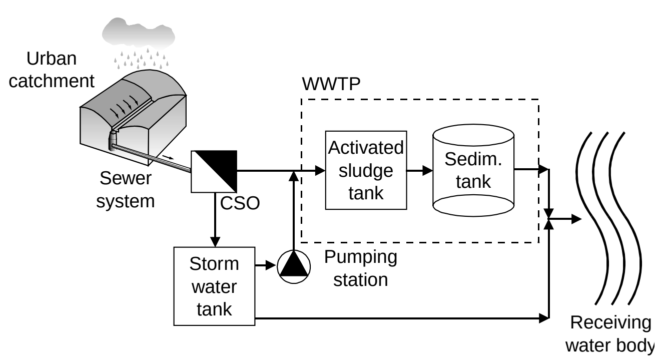


**Figure 1** | Schematic representation of the integrated urban drainage system.

The hydrological–hydraulic module starts to evaluate the net rainfall, from the measured hyetograph, by a loss function (taking into account surface storage and soil infiltration). From the net rainfall, the model simulates the net rainfall–runoff transformation process and the flow propagation with a cascade of one linear reservoir and a channel (representing the catchment) and a linear reservoir (representing the sewer network). This simplified approach provided good results in several applications even when compared with more detailed approaches (Mannina *et al.* 2004; Mannina 2005; Freni *et al.* 2008*a*). The solid transfer module reproduces the build-up and wash-off of pollutants from the catchment and the propagation of solids in the sewer network considering also their sedimentation and re-suspension. CSO structures are simulated by means of the continuity equation and a rating curve equation describing the hydraulic behaviour of the overflow (Mannina 2005). The second sub-model is aimed at the analysis of WWTP during both dry and wet weather periods. The WWTP sub-model simulates the behaviour of the part of the plant composed by an activated sludge tank and a secondary sedimentation tank. For the activated sludge tank model, mass balance equations derived from Monod's theory have been used in order to reproduce pollutant (BOD, COD, TSS) removal (Metcalf & Eddy 1991). The sedimentation tank was simulated using the solid flux theory and the settling velocity function according to Takács *et al.* (1991). In particular, the solids concentration profile has been simulated by dividing the settler into a number of horizontal layers. Within each layer the concentration is assumed to be constant and the dynamic update is performed by imposing a mass balance for each layer. The third sub-model examines the assessment of RWB. As aforementioned, two river water quality modelling approaches, developed in previous studies (e.g. Mannina & Viviani 2010*b*,*c*), have been incorporated in the integrated bespoke urban drainage model: a detailed model approach and a simplified one. The former is based on the completed form of the Saint-Venant equation for the propagation of the flow along the river (quantity module) and the 1D advection–dispersion equation for the assessment of the pollutant loads (DO, BOD, $NH_4$, and NO) (quality module). Specifically, the solution of the Saint-Venant equations is obtained by means of an explicit scheme based on space-time conservation. The method considers the unification of space and time and the enforcement of flux conservation in both space and time. On the other hand, concerning the quality sub-model it is based on the 1D advection–dispersion equation. Particularly, the principle of upstream weighting applied to finite difference methods is employed. Such a method enables us to reduce the numerical dispersion, avoiding oscillation phenomenon. The optimal weighting coefficient has been calculated on the basis of the mesh Peclet number.

The SRWQ is based on the reservoir modelling concept. As for the detailed approach, the SRWQ is divided into two sub-modules: a quality and a quantity module. The model employs a river schematisation that considers different stretches according to the geometric characteristics and to the gradient of the river bed. Each stretch is represented with a conceptual model of a series of linear channels and reservoirs. The channels determine the delay in the pollution wave and the reservoirs cause its dispersion. As for the DRWQ, to assess the river water quality, the model employs four state variables: DO, BOD, $NH_4$, and NO.

With regards to the quality processes both modelling approaches (SRWQ and DRWQ) take into the main physical/chemical processes (Figure 2): degradation of dissolved carbonaceous substances; ammonium oxidation; algal uptake and denitrification; dissolved oxygen balance, including depletion by degradation processes and supply by physical reaeration and photosynthetic production.

For the sake of conciseness, the descriptions of the model algorithms are remanded to literature (see, Mannina 2005; Mannina & Viviani 2010*b*,*c*).

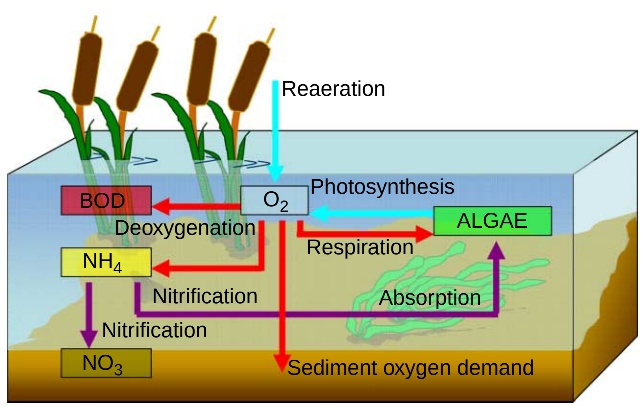


**Figure 2** | Quality sub-module modelled processes.

## UNCERTAINTY ANALYSIS: THE GLUE METHODOLOGY

GLUE methodology has been used for the study purpose (Beven & Binley 1992). The GLUE methodology is attractive because there is no need for detailed distribution functions of the observable variables and of errors when the explicative models provided are complex or the number of parameters is high (Mantovan & Todini 2006). However, it must be stressed that such methodology relies on some subjective hypotheses that could prevent its objective application (Freni *et al.* 2008*b*, 2009*c*). The GLUE is a Monte Carlo based technique that enables the assessment of uncertainty. The GLUE differs from traditional Bayesian approaches to uncertainty analysis in that the likelihood measure need not be based on a formal error model. Furthermore, GLUE is advantageous, as it is quite difficult to differentiate between different sources of errors, e.g., input errors, model structural errors, observation data errors, parameter errors, etc. By treating the different sources of error implicitly using the GLUE likelihood weighting approach, it is possible to assess the potential of the sample of behavioural models to simulate the observations with a minimal need for additional assumptions (Thorndahl *et al.* 2008). Indeed, 'the likelihood measure value is associated with a parameter set and reflects all these sources of error and any effects of the covariation of parameter values on model performance implicitly' (Beven & Freer 2001). The GLUE considers a random generation of parameter sets and identifies multiple parameter sets with different probabilities. The generation of multiple parameter sets is accomplished by means of the Monte Carlo approach to sample the uncertain parameter space. The performance of model predictions associated with each randomly generated parameter set is assessed by means of a likelihood measure. Parameter sets with poor likelihood weights are classified as non-behavioural and they can be rejected. All other weights from behavioural or acceptable runs are retained and re-scaled so that their cumulative total sums to unity. The GLUE procedure thus transforms the problem of searching for an optimum parameter set into a search for sets of parameter values that give reliable simulations. 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 GLUE approach relies on the concept of equifinality, which maintains that, due to the errors inherent in the model structure (e.g. due to simplification and aggregation), errors in observed data and the difficulty in determining an exact error model, it is inappropriate to perform calibration based on an optimum set of parameters.

In the literature, the most frequently used likelihood measure for GLUE is the Nash–Sutcliffe coefficient (e.g. Nash & Sutcliffe 1970; Freer *et al.* 1996; Beven & Freer 2001), which is also used in this paper:

$$E_j = 1 - \frac{\sum_{i=1}^{n}(O_i - P_i)^2}{\sum_{i=1}^{n}(O_i - \bar{O})^2} \qquad (1)$$

where $O$ is observation; $P$ is model prediction; $\bar{O}$ is mean value of model predictions and observations, respectively, and $n$ is the number of observations; the subscript "$j$" indicates the state analysed variable (in this study, Q, BOD and DO have been considered as model outputs). Like other likelihood measures, the Nash–Sutcliffe index is equal to or lower than zero for all simulations that are considered to exhibit behaviour dissimilar to the system under study, and it increases monotonically as the similarity in behaviour increases, with a limit value equal to 1, which represents the better model performance.

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 belief of the modeller in that set of parameter values as a simulator of the system. The degree of belief is derived from the predicted variables arising from that set of parameter values. Treating the distribution of likelihood values as a probabilistic weighting function for the predicted variables, therefore, allows an assessment of the uncertainty associated with the predictions, conditioned on the definition of the likelihood function, input data and model structure used.

A method of deriving predictive uncertainty bands using the likelihood weights from the behavioural simulations has been shown by Beven & Binley (1992). The uncertainty bands are calculated using the 5% and 95% percentiles of the predicted output likelihood weighted distribution. The uncertainty bands width is an indirect measure of the uncertainty connected with modelling approach; the uncertainty bands should always contain the majority of the observations, otherwise the model structure must be rejected. Wider bands indicate higher uncertainty in the estimation of the modelling output and thus lower confidence in the model results. Conversely, smaller bands containing the observations indicate reliable and robust modelling approaches.

## THE CASE STUDY

The integrated model and the uncertainty analysis have been applied to the catchment of the Savena river (Italy). 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 long and it receives discharge from six CSOs deriving from the Bologna sewer network (Figure 3). 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 an 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 five of these have water quality aspects been analysed regarding both RWB and SS. The monitoring infrastructure consisted of three raingauges, eight sonic level gauges and six automatic 24-bottles samplers (three in the sewer system and three in the river). The study has been focused on $BOD_5$, TSS, COD and DO, even if analogous considerations may be extended to other parameters. In this study, only a part of the Savena River has been simulated (400 metres downstream of the CSO No. 6) because the contribution of this particular CSO to river pollution has been determined significant compared to all the others. The contribution of other polluting sources has been considered by monitoring river, pollution load in the first cross-section upstream of CSO No. 6 and introducing this information as input in the models. Savena is an ephemeral river, since there are wide flow variations during the different seasons and the river base flow is comparable with the CSO discharge. Further details on the monitoring campaign can be found in Artina *et al.* (1999).


**Figure 3** | Savena catchment.

## METHODOLOGY APPLICATION

As discussed above, two river water quality modelling approaches have been tested by incorporating them into an integrated bespoke urban drainage model in order to evaluate their uncertainty. This analysis helps gain insight about the level of accuracy that has to be provided for a correct assessment of the quality state of ephemeral rivers.

In order to compare the two different river quality modelling approaches, 10,000 Monte Carlo simulations have been run for each approach varying both quantity and quality parameters of the RWB sub-models. Conversely, the parameters of the other sub-models (SS and WWTP) have been kept constant in order to focus only on the RWB modelling. Thereafter the uncertainty bands have been assessed for both modelling approaches to enable highlighting the differences among them. In particular, by means of the Monte Carlo simulations each parameter value has been drawn from ranges obtained by the calibration of the five fully monitored events. The model has been calibrated over single events: upstream sub-models' parameters have been calibrated first and then kept constant during the calibration of downstream ones. Analogously, water quantity modules have been calibrated first and then kept constant during the calibration of the quality ones.

**Table 1** | Main values of the integrated model parameters

| Parameter | Symbol | Unit | Value |
|---|---|---|---|
| Initial hydrological losses | $W_0$ | mm | 0.3 |
| Catchment runoff coefficient | $\Phi$ | – | 0.4 |
| Catchment reservoir constant | $K_1$ | min | 20 |
| Sewer reservoir constant | $K_2$ | min | 25 |
| Daily accumulation rate | Accu | Kg/(ha d) | 8 |
| Decay rate in the Alley-Smith model | Disp | $d^{-1}$ | 0.07 |
| Wash-off coefficient | Arra | $mm^{-Wh} h^{(Wh-1)}$ | 0.18 |
| Wash-off factor | Wh | – | 0.64 |
| Erosion coefficient | $M$ | g/s | 108 |
| Sewer suspension delay | $K$susp | h | 0.07 |
| Sewer bed transport delay | $K$bed | h | 0.3 |
| CSO first dilution factor | $r_{d1}$ | – | 3 |
| CSO second dilution factor | $r_{d2}$ | – | 5 |

The system geometry has been considered known and unaffected by errors.

A description of model parameters and model calibration and validation is discussed in detail in previous studies (Mannina 2005; Freni *et al.* 2008*a*; Mannina & Viviani 2010*a*). In Table 1 the main model parameters obtained by model calibration previously developed and employed for the present application are reported.

Parameter variation ranges used for the uncertainty analysis have been reported in Table 2. Such ranges were selected as that one strictly including the calibrated values obtained for all five Savena events (Beven & Binley 1992; Freni *et al.* 2009*b*). In order to better pin down the most sensitive model parameters a preliminary sensitivity analysis was performed. This analysis has been carried out generating 10,000 random sets of parameters considering their distribution uniform, without any prior knowledge about them and using these sets to perform model simulation. For each of these simulations a performance index has been evaluated in the form of Nash and Sutcliffe Efficiency Criterion (1970). Equifinality indicates either prediction insensitivity to parameters or that some parameters are interacting closely in producing behavioural models. In order to detect the above issue, a correlation matrix has been worked out for the model parameters. The correlations between most parameters are somewhat small. The weaker correlations in GLUE also indicate the phenomenon that the real response surface is flattened by GLUE. This is in accordance with other analyses of the GLUE methodology (Mantovan & Todini 2006).

## RESULTS

In the following, for example's sake, considerations will be based on graphs obtained for the rainfall event of 28 November 1998; similar behaviour has been obtained for all

**Table 2** | Parameter ranges of the employed models in the Monte Carlo sampling

| | Parameter | Lower limit | Upper limit |
|---|---|---|---|
| SRWQ | Linear channel constant $\lambda$ (s) | 250 | 2,000 |
| | Quantity reservoir constant $k$ (s) | 150 | 300 |
| | Quality reservoir constant $k_c$ (s) | 150 | 300 |
| | Deoxygenation coefficient $k_D$ ($s^{-1}$) | 0.001 | 0.008 |
| | Reaeration constant $k_R$ ($s^{-1}$) | 0.002 | 0.009 |
| | Oxygen actual production Ph ($gO_2\,L^{-1}s^{-1}$) | 0.02 | 0.045 |
| | Respiration ($gO_2\,L^{-1}s^{-1}$) | 0.02 | 0.045 |
| DRWQ | River bed roughness $k_s$ ($m^{1/3}s^{-1}$) | 20 | 100 |
| | Longitudinal dispersion coefficient $D_L$ ($m^2\,s^{-1}$) | 0.01 | 20 |
| | Deoxygenation coefficient $k_D$ ($s^{-1}$) | 0.001 | 0.01 |
| | Reaeration constant $k_R$ ($s^{-1}$) | 0.003 | 0.2 |
| | Oxygen actual production Ph ($gO_2\,L^{-1}\,s^{-1}$) | 0.02 | 0.045 |
| | Respiration $r$ ($gO_2\,L^{-1}\,s^{-1}$) | 0.02 | 0.045 |

the simulated events. The selected event is characterised by an antecedent dry weather period (ADWP) of 3.8 days and a rainfall volume, maximum intensity, average intensity and duration of 4 mm, 4 mm/h, 1.2 mm/h and 200 minutes, respectively.

Figure 4 shows scatter plots for the likelihood (L) based on Nash and Sutcliffe for selected parameters sampled both for the DRWQ and for the SRWQ. Each dot represents one run of the model with different randomly chosen parameter values within the ranges of Table 2. The generation of the likelihood surface involves a decision about the criterion for model rejection; actually the uncertainty bounds associated with the retained simulations will depend on the choice of the likelihood measure and rejection criterion. Particularly, simulations that achieve a likelihood value less than zero are rejected as non-behavioural. The remaining simulations are rescaled between 0 and 1 in order to calculate the cumulative distribution of the predictive variables. As pointed out in the previous paragraph, 10,000 Monte Carlo simulations were run for both approaches. Among the 10,000 Monte Carlo simulations, 6,545 and 4,891 were behavioural, respectively, with regards to the SRWQ and DRWQ approach. The most sensitive parameters of the detailed modelling approach are the ones connected to the processes of deoxygenation and reaeration. Indeed, Figure 4(c) shows a strong sensitivity of the oxygen to the reaeration coefficient ($K_R$). Conversely, the processes which are related to the oxygen contribution due to photosynthesis phenomenon are less sensitive (Figure 4(f)). Such results are in agreement with the physics of the phenomenon. Indeed, during storm events, especially for an ephemeral river such as the Savena, the largest contribution of oxygen comes from the reaeration with the atmosphere due to the intense flow turbulence. This aspect is reflected in terms of reaeration coefficient values. In particular, these latter are some orders of magnitude higher with respect to the dry weather ones. This aspect confirms the important role played by the flow turbulence during storm weather. The intense turbulence is obviously caused by the high increment of the river flow with respect to the dry weather flow. Such an increment can be of some orders of magnitude and it is due, especially for the ephemeral river, to the intermittent discharges coming from the urban sewer systems, i.e. the CSOs. This is the case also for the selected case study (Figure 5), where the RWB flow rate during the wet weather rises up to 0.3 m$^3$/s, so becoming approximately an order of magnitude higher with respect to the dry weather one (0.02 m$^3$/s). Furthermore, these variations between dry and wet weather periods require the recurrence to model approaches that employ dynamic models both for the quantity and for the quality aspects. These dynamic models should consider a narrow temporal time scale due to the fact that the involved phenomena occur in a short time (acute pollution, i.e. the effects last for a period comparable to that of the rainfall). Such a requirement can not always be fulfilled by the

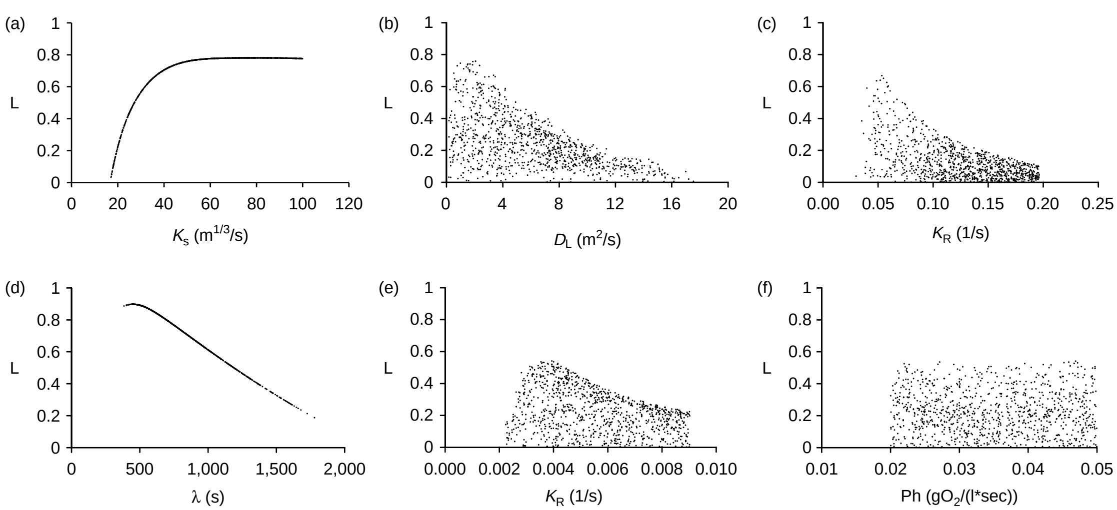


**Figure 4** | Scatter plots for some parameters of the detailed model approach [(a), (b), (c)] and of the simplified model approach [(d), (e), (f)].

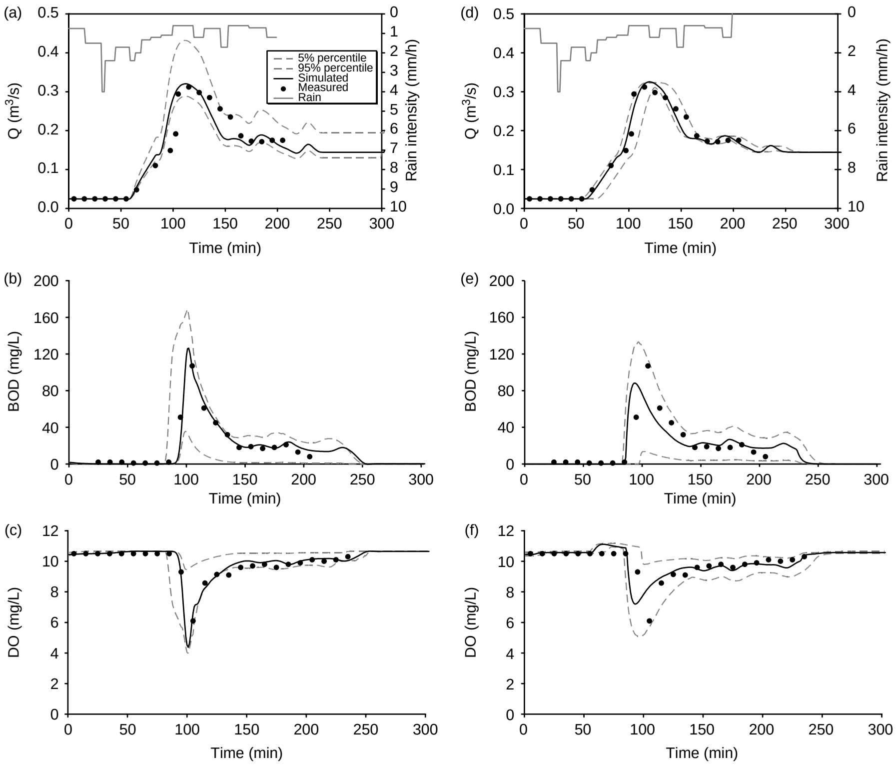

**Figure 5** | Uncertainty bands in terms of flow rate, BOD, and DO for the detailed model [(a), (b), (c)] and for the simplified model approach [(d), (e), (f)].

available commercial models that generally consider daily time scale; indeed, lower time scale resolutions are not feasible due to large computational time.

Figure 5 shows the model results in terms of flow and concentrations (BOD and DO) for the two modelling approaches. More specifically, Figure 5(a–c) regard the detailed approach whereas Figure 5(d, e) refer to the simplified approach. As can be observed, both models show a good capability to fit the experimental data, giving the impression that all adopted approaches are equivalent both for the quantity and for the quality. However, in terms of uncertainty bounds some differences can be addressed. The uncertainty bounds of the detailed model for the quantity module are wider than the corresponding simplified approach ones. On the other hand, the quality uncertainty bounds of the simplified approaches are wider with respect to the detailed ones. Furthermore, for the simplified models the simulations of the BOD and DO are poorer. The detailed approach appears to be more robust with respect to the simplified one, showing generally narrower bounds and small discrepancies with the measured data. However, bearing in mind the uncertainty of the measured data, the simplified approach can be also considered acceptable. Further, the simplified approach is preferable due to the lower computational time (three orders of magnitude faster with respect to the detailed one). In conclusion, both approaches are revealed to be suitable to fulfil the research goal, the RWB quality state assessment. The approach choice has to be addressed by the accuracy level required for the research that has to be carried out: less uncertainty and higher accuracy are better addressed by employing the detailed approach. However, in case of long-term simulations as well as uncertainty analysis, computational time may prevent the application of detailed approach, and in this case the simplified approach can be a good solution to cope with such shortcomings.

## CONCLUSIONS

This study considered the comparison between detailed and simplified modelling approaches for the assessment of the RWB quality state considering an integrated modelling approach. More specifically, the complete form of the Saint-Venant equations along with the 1D advection–dispersion equations have been compared with a simplified reservoir model approach. The comparison has been accomplished in terms of uncertainty analysis. This latter has been assessed by means of the GLUE methodology. The results reveal that both models have a good capability to fit the experimental data, giving the impression that all adopted approaches are equivalent both for the quantity and for the quality. The detailed model approach is more robust and presents less uncertainty in terms of uncertainty bands. On the other hand, the simplified river water quality model approach shows higher uncertainty and may be unsuitable for RWB quality state assessment. However, the model approach accuracy level is strictly connected with the research goal. Therefore, the simplified model approach can be suitable and fulfil the study needs, although less accurate in terms of uncertainty than the detailed one. In other words, the choice of the model approach has to be compared with the research goal. Whenever possible, simplified approaches are preferable to detailed ones since they require reduced amount of model parameters and computational times. Therefore, for the assessment of model uncertainty, due to the fact that generally several Monte Carlo simulations are needed, simplified approaches may constitute an attractive solution to cope with the long-term computational time of the detailed models.

## ACKNOWLEDGEMENTS

Authors gratefully acknowledge Prof. Sandro Artina and Dr Marco Maglionico (D.I.S.T.A.R.T.–University of Bologna, IT) for providing data on Savena catchment. The authors would like also to thank Eng. Giuseppe Serio for his precious help in developing the research.

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