A parsimonious dynamic model for river water quality assessment

Giorgio Mannina and Gaspare Viviani

ABSTRACT

Water quality modelling is of crucial importance for the assessment of physical, chemical, and biological changes in water bodies. Mathematical approaches to water modelling have become more prevalent over recent years. Different model types ranging from detailed physical models to simplified conceptual models are available. Actually, a possible middle ground between detailed and simplified models may be parsimonious models that represent the simplest approach that fits the application. The appropriate modelling approach depends on the research goal as well as on data available for correct model application. When there is inadequate data, it is mandatory to focus on a simple river water quality model rather than detailed ones. The study presents a parsimonious river water quality model to evaluate the propagation of pollutants in natural rivers. The model is made up of two sub-models: a quantity one and a quality one. 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. To assess the river water quality, the model employs four state variables: DO, BOD, NH_4, and NO. The model was applied to the Savena River (Italy), which is the focus of a European-financed project in which quantity and quality data were gathered. A sensitivity analysis of the model output to the model input or parameters was done based on the Generalised Likelihood Uncertainty Estimation methodology. The results demonstrate the suitability of such a model as a tool for river water quality management.

Key words | mathematical modelling, physical-chemical water quality, sensitivity analysis, simplified model

Giorgio Mannina (corresponding author)
Gaspare Viviani
Dipartimento di Ingegneria Idraulica ed Applicazioni Ambientali,
Università di Palermo,
Viale delle Scienze,
90128 Palermo,
Italy
E-mail: *mannina@idra.unipa.it*

INTRODUCTION

In recent years, the use of mathematical models in river water quality management has become a common practice to rebuild the cause-effect relationship between emissions and water body quality and to design as well as assess the effectiveness of mitigation measures (Rauch *et al.* 1998; Shanahan *et al.* 1998; Reichert *et al.* 2001; Shanahan *et al.* 2000). Two different model approaches are generally adopted: detailed and simplified. The former involves sophisticated models that employ several algorithms each representing a physical/chemical process and therefore tends to be affected by over-parameterisation (i.e. there are too many parameters to quantify). On the other hand, the simplified approach limits both the number of model algorithms and parameters. Detailed approaches generally are characterised by prohibitive computational time that limits their effective applicability. A possible middle ground between detailed and simplified models may be parsimonious models that represent the simplest approach that fits the application (Harremoës & Madsen 1999). Therefore, parsimonious models are an attractive alternative to

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detailed approaches due to the fact that they have the advantage of a lower level of over parameterisation and a higher level of parameter identification (Beck 1999; Freni *et al.* 2009). When employing such models, the goal is to reduce the complexity and effort spent on computation and analysis. Tailoring a model type for a certain application depends on the project objectives and the data availability (Marsili-Libelli & Giusti 2008). Detailed models are very useful for short-term simulations of representative events (Radwan *et al.* 2003). The necessary computation time of detailed models can be a deterrent for use in long-term statistical information applications or as a management tool. Dekissa *et al.* (2004) suggested employing simplified models to assess river water quality when there is a lack of data. Radwan *et al.* (2003) compared the results of a detailed and a simplified river water quality model and stated that the conceptual simplified model is 1,800 times faster than the detailed Mike11 model. The conceptual simplified model is recommended for long-term simulations since it includes only the most important and sensitive processes and is calibrated against results from the detailed model.

The literature has numerous examples of water quality models. The complexity and number of parameters used in each varies, and some examples include: QUAL2E (Brown & Barnwell 1987), WASP5 (Ambrose *et al.* 1993), CE-QUAL-W2 (Cole & Buchak 1995), HEC-5Q (USACE 1986), SIMCAT and TOMCAT (Jamieson & Fedra 1996), QUASAR (Whitehead *et al.* 1997), and MIKE11 (DHI 1992). The latter model does not include the necessary Water quality (WQ) module and is used mainly for the Urban Pollution Management (or UPM) the Research Programme adopted in the UK (Crabtree *et al.* 1996). MIKE11 is made up by modules that may be combined and simulates advection–dispersion, water quality, sediment transport, eutrophication, and rainfall-runoff. SIMCAT and TOMCAT, which are models generally used by the Environmental Agency, are rarely cited the literature likely because they are not used for regulation outside of the UK. This is probably due to their stochastic component as well as a lack of commercial exposure (Cox 2003). On the other hand, the ISIS model, which was developed in the UK by HR Wallingford & Sir William Halcrow & Partners Ltd (1998), is a dynamic model used by the Environmental Agency capable of simulating flow and water-quality, but is used more as a flow model for flood defence groups than for water-quality modelling. According to Cox (2003) US modelling practises tend towards steady-state models while UK models generally use stochastic techniques, although these two are not mutually exclusive.

Rahman & Salbe (1995) modelled the impacts of diffuse and point source nutrients on the water quality of the South Creek catchment in Australia using HEC-5Q. Wu *et al.* (1996) simulated the investigating effect of reservoir operation on water quality using WASP. Tufford & McKellar (1999) used spatial–temporal definition and WASP to analyse the water quality of a large reservoir on the South Carolina coastal plain in the United States. Among the existing water quality models, QUAL2E, developed and released by the United States Environmental Protection Agency (USEPA) in 1985, is one of the most popular models (Cox 2003). It is an enhanced steady-state model used mainly to simulate the inflow and water quality of rivers and streams. The basic theory of QUAL2E is based on the assumption that the major transport mechanisms, advection and dispersion, are significant only along the main direction of flow (Brown & Barnwell 1987). The International Water Association (IWA) river water quality task group proposed the River Water Quality Model No. 1 (RWQM1) (Reicher *et al.* 2001). This model is based on the Chemical Oxygen Demand (COD) concept to be compatible with the activated sludge model (ASM) Henze *et al.* (2000) developed for wastewater treatment plant modelling and also to enable interconnections among the models for a holistic approach (i.e. sewer system, wastewater treatment plant, and receiving water body). Nevertheless, RWQM1 is considered too comprehensive and complicated to be applicable in when there is limited available data, which is a quite common case.

The aforementioned models are generally too comprehensive and complex to be applied directly in many situations where there are limited available data (Deksissa *et al.* 2004). The number of state variables and parameters are generally large and it is difficult to find sufficient and reliable data to calibrate the parameters. Thus, model simplification is necessary (Vanrolleghem *et al.* 2001). In data poor situations, one needs to focus on a simple river water quality model that accounts for both mass and elemental balances.

The goal of this study is therefore to present a parsimonious WQ model aimed at simulating the pollutant propagation in natural rivers to propose a possible tool for river water quality management. Different river stretches are modelled according to the geometric characteristics and to the gradient of the riverbed. Each stretch is represented by a conceptual model of a series of linear channels and reservoirs. The channels determine the delay in the pollution wave and the reservoirs describe its dispersion. For the assessment of the river water quality, the model employs four state variables: DO, BOD, NH_4, and NO. The model was applied to the Savena River (Italy), which was the focus of a European-financed project in which quantity and quality data were gathered. The results suggest that the model is a possible tool for river water quality management.

MATERIALS AND METHODS

Study site

The river studied in this work and the field data gathering campaign were part of an earlier European-financed project (Artina *et al.* 1998, 1999). A short description of the system is reported given herein, but more detailed information is available in previous studies (Artina *et al.* 1998, 1999).

The Savena is a rural ephemeral river that passes through a number of small towns before entering the southern neighbourhood of Bologna (Figure 1). The catchment area of the Savena, at the downstream boundary of the studied river reach, is nearly 160 km^2. The river is characterised by a very variable hydraulic regime with discharge usually ranging from a few litres per second during dry summer periods, up to several cubic meters per second during wet weather.

The studied river reach is about 6 km long, receiving six CSO discharges from the Bologna sewer network and twelve from the San Lazzaro sewer systems, a small centre in the surrounding area of Bologna. The CSOs generally operate during small intensity rainfalls and, in many cases, their discharge is similar to the river's discharge. The sewer network is a part of the combined system serving the whole city of Bologna, which can be treated as hydraulically divided into many independent catchments, all connected to a WWTP. The city of Bologna has about

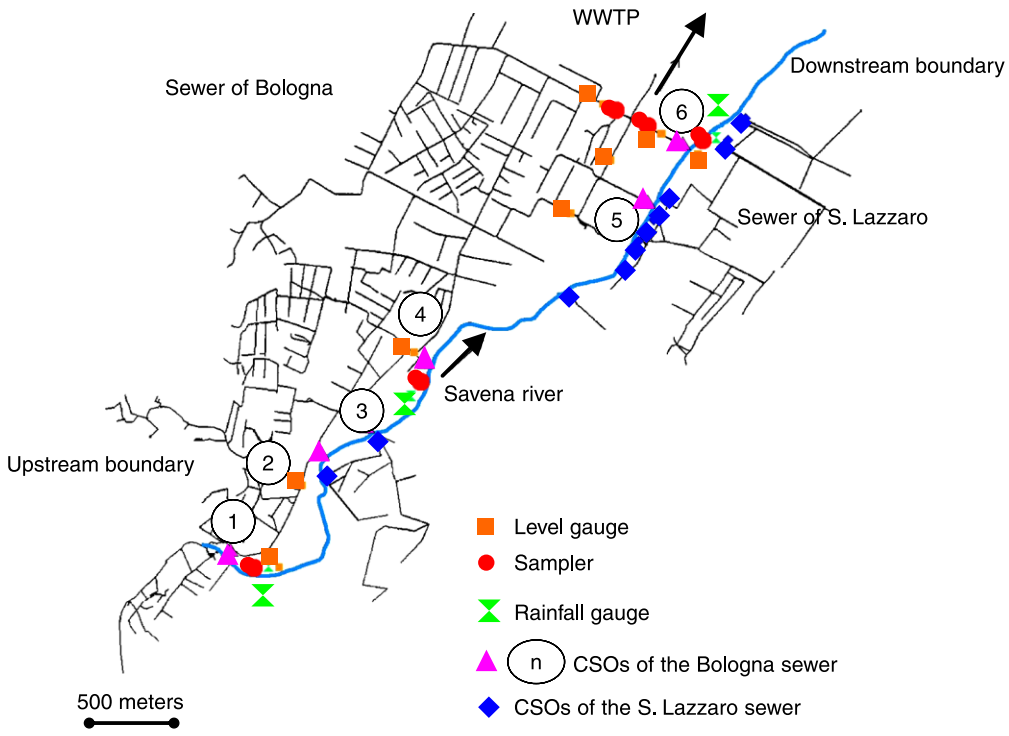

Figure 1 | Savena catchment.

500,000 inhabitants and an equivalent population of about 800,000 inhabitants.

Only the part of this catchment, which has an effect on the studied reach of the Savena River, has been taken into account. This part of Bologna has an area of more than 450 ha, with an impervious percentage of about 66% and about 60,000 inhabitants. The six CSOs are installed corresponding to the different cross-sections of the main sewer in pipes with different sizes and shapes ranging from egg shaped 80 × 120 cm up to polygonal shaped 260 × 208 cm. The sewer system of San Lazzaro, on the right side of the Savena River drains a catchment of about 120 ha with 10,000 inhabitants. About 50 events were recorded during an experimental survey from December 1997 to July 1999, but water quality aspects were analysed for both RWB and SS for only five of these. The analysed parameters were as follows: BOD_5, NH_4, TSS, COD, pH, dissolved oxygen (DO), temperature, and conductivity. The considered events are characterised by small rainfall volumes with rapidly varying intensities. Those events are only partially representative of the climatic conditions in the Bologna area that are typically characterised by a high frequency of small events in winter and spring, by intense and short events in early autumn, and a long dry period between May and September. Nevertheless, those events are representative of the real catchment situation in terms of polluting loads: high frequency and small rainfall volume events activate CSOs. During the five monitored events only one of the six CSOs discharged to the river (CSO No. 6), and for this reason results are presented only for the last trunk of Savena urban reach (400 m downstream of the CSO). Even if the analysed river reach is rather short, the measured data show that especially during storm events, its ephemeral behaviour and significant turbulence associated with flood events guarantee sufficient depletion of polluting concentrations (Mannina & Viviani 2009).

Because the analysed urban area is 5.7 km^2, which is equivalent to 3.2% of the total catchment surface, the contribution of the upstream polluting sources was determined by monitoring the pollution load in the first cross-section upstream of the urban area and using this information as input for the models.

MODEL DESCRIPTION

The proposed model is aimed at the pollutant propagation simulation and is based on a principle of a scheme of reservoirs and linear channels (Figure 2). The model is divided into two sub-models: a quantity one and a quality one. The former models the flow propagation along the river while the second one models the pollution of the BOD, DO, NH_4, and NO. As mentioned above, the aim is to develop a river water quality management tool that is characterised by limited computational time (i.e. time in the order of minutes). For example, when modelling backwater effect of weirs or other hydraulic controls like tidal effects, complex models (i.e. as hydrodynamic models) are usually employed. Such models may be based on the St. Venant equations that are computationally demanding. In the absence of the tidal effect, such complex hydraulic models can be simplified into a conceptual hydraulic model. For the quantity sub-model during a flow propagation process, the hydrograph is characterised by two main relevant phenomena: a hydrograph flow delay and a hydrograph flow reduction. The former was modelled considering the time lag between the centroid of the input and the centroid of the output and is characterised by a linear channel constant (λ, Willems 2000). However, the flow peak reduction was simulated using a Continuously Stirred Reactor in Series (CSRS) and is characterised by a reservoir constant k (Whitehead *et al.* 1979; Cunge *et al.* 1980; Chapra 1997). The river is sub-divided into sections in which the geometric characteristics of the riverbed and the hydraulic characteristics of the flow are held to be constant.

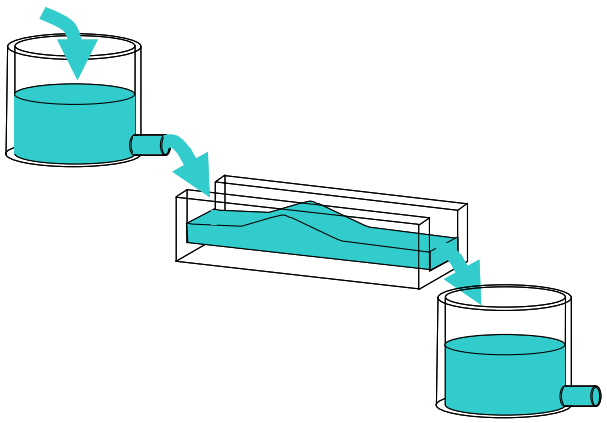

Figure 2 | Quantity sub-model scheme.

The flow in reach i is calculated with the following expression:

$$\begin{cases} Q_{out}(t) = Q_{in}(t) - k \cdot \frac{dQ_{out}(t)}{dt} \\ Q_{out}(t) = Q_{in}(t-\lambda) \end{cases} \Rightarrow Q_{out}(t) = Q_{in}(t-\lambda) - k \cdot \frac{dQ_{out}(t)}{dt} \quad (1)$$

The explicit solution of the above equation may be obtained employing the Adams-Moulton scheme, which gives the following expression for the flow rate at the outlet of the system of Equations (1) to assess the outflow rate as (Numerical Recipes 1986):

$$\begin{cases} Q_{out}(t) = \alpha \cdot (Q_{in}(t-\lambda-1) + Q_{in}(t-\lambda)) + Q_{out}(t-1) \cdot \beta \\ \alpha = \Delta t/(\Delta t + 2k) \\ \beta = (\Delta t - 2k)/(\Delta t + 2k) \end{cases} \quad (2)$$

where Δt is the time step, Q_{in} is the influent flow, Q_{out} is the effluent flow, k is the reservoir constant, λ is the linear channel constant, and α and β are coefficients.

The above method employed for the quantity aspects was used to simulate the quality phenomena. More specifically, a mass balance equation was used for each pollutant modelled, namely BOD, DO, NH_4, and NO. According to the modelling concept employed the generic pollutant mass at the effluent was evaluated according to the following equations:

$$\begin{cases} C_{out\_t} = \frac{\alpha_c (Q_{in\_t} \cdot C_t + Q_{in\_t-1} \cdot C_{t-1}) + \beta_c \cdot C_{out\_t-1} \cdot Q_{out\_t-1}}{Q_{out\_t-1}} \\ \alpha_c = \Delta t/(\Delta t + 2k_c) \\ \beta_c = (\Delta t - 2k_c)/(\Delta t + 2k_c) \end{cases} \quad (3)$$

where C_{out_t} and C_{out_t-1} are the concentration of the generic pollutant at the outlet at time t and at time $t-1$, respectively; Q_{out_t} and Q_{out_t-1} are the concentration of the generic pollutant at the outlet at time t and at time $t-1$, respectively; k_c is the quality reservoir constant; Δt is the time step; α_c and β_c are coefficients.

The quality sub-model is devoted to the evaluation of the river quality state; in Figure 3 a schematic overview of the most dominant processes is provided. Four state variables are simulated: DO, BOD, NH_4, and NO. There are basically two DO sources: reaeration from the atmosphere and photosynthesis of algae and plants. However, DO is consumed via plant respiration, nitrification processes, and BOD degradation. All processes are described assuming 1st order kinetics. The main equations employed for the simulations of the BOD decay process are:

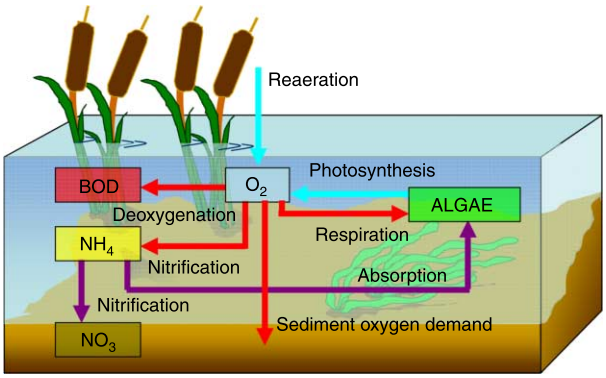

Figure 3 | Quality sub-model scheme.

$$BOD_t = \frac{Q_{in\_t} BOD_{t-1} \cdot e^{-K_D \cdot \Delta t}}{Q_{out\_t}} \quad (4)$$

$$K_D = K_{D(20°)} \cdot \vartheta_D^{(T-20)} \cdot \frac{DO}{K_s + DO} \quad (5)$$

where K_D is the deoxygenation coefficient, ϑ_D is the Arrhenius temperature coefficient of the degradation process, T is the temperature, and K_s is the half saturation constant for the BOD.

The ammonium (NH_4) and the nitrate (NO) major processes modelled are nitrification, photosynthesis due to algae, and respiration:

$$NH_{4_t} = \frac{Q_{in\_t}(NH_{4_{t-1}} \cdot e^{-K_N \cdot \Delta t} - y_{resp}(P_h - r)}{Q_{out\_t}} \quad (6)$$

$$K_N = K_{N(20°)} \cdot \vartheta_N^{(T-20)} \cdot \frac{NH_4}{K_{s\_NH_4} + NH_4} \quad (7)$$

$$NO_t = \frac{Q_{in\_t}(NO_{t-1} + K_{Den}(NH_{4_{t-1}}(1 - e^{-K_N \cdot \Delta t})) - NO_{t-1} \cdot e^{-K_{Den} \cdot \Delta t})}{Q_{out\_t}} \quad (8)$$

where K_N is the nitrogen coefficient, K_{Den} is the denitrification coefficient, ϑ_N is the Arrhenius temperature coefficient of the nitrification process, K_{s_NH4} the half saturation constant for the ammonium, P_h is the actual production of oxygen due to photosynthesis, and r the reareaction coefficient.

As aforementioned, the quality sub-model for the simulation of DO considers the main processes that occur

in the aquatic environment; in particular, the photosynthesis of algae and plants, the re-aeration through exchange with the atmosphere, the DO consumption by plant respiration, animals and bacteria, the BOD degradation process, the sediment oxygen demand, and oxidation. Therefore, the DO was modelled according to the following equation:

$$DO_{\_t} = \frac{1}{Q_{out\_t}} \begin{pmatrix} DO_{sat} - \frac{1}{2}(DO_{sat} - DO_{t-1}) \cdot e^{-K_R \Delta t} \\ -\frac{1}{2}\frac{K_D}{K_R - K_D} BOD_{t-1}(e^{-K_D \cdot \Delta t} - e^{K_R \Delta t}) \\ -\frac{1}{2} Y_{Nitr} \cdot \frac{K_N}{K_R - K_N} NH_{4_{t-1}}(e^{-K_N \cdot \Delta t} - e^{K_R \Delta t}) \\ +(P_h - r) \cdot \Delta t \end{pmatrix} \quad (9)$$

where DO_{sat} is the saturation concentration of DO, K_R is the reaeration constant, Y_{Nitr} is the yield factor describing the amount of oxygen used for nitrification.

MODEL APPLICATION

The model was applied considering the five events of the Savena case study separately. The calibration was done in two steps. In the first step, the hydraulic parameters were evaluated considering the measured flow data. In the second step, the quantity parameters were set to the calibration values to assess the quality parameters. The model parameter estimation was carried out using the Generalised Likelihood Uncertainty Estimation (GLUE) methodology (Beven & Binley 1992). GLUE is a Monte Carlo simulation approach developed as an attempt to recognise more explicitly the underlying uncertainties of models simulating environmental processes. The GLUE approach rejects the concept of an optimum parameter set and assumes that, prior to the input of data into a model, all parameter sets have an equal likelihood of being acceptable estimators of the system in question. Many parameters sets are generated from specified ranges using Monte Carlo simulation. The performance of individual parameter sets is then assessed via likelihood measurements, which are used to weight the predictions of the different parameter sets. This includes the rejection of some parameter sets as non-behavioural. All other weights from behavioural or acceptable runs are retained and rescaled so that their cumulative total is equal to 1. The cumulative likelihood weighted distribution of predictions can then be used to estimate quantiles for the predictions at any time step.

The likelihood measure represents the ability of the model to fit real data. The acceptability threshold Tr represents a user-defined critical value indicating the minimum value of the likelihood measure that each

Table 1 | Variation ranges of some model parameters and maximum efficiency values

Parameter	Unit	Lower limit	Upper limit	Max efficiency	References
Lag time (λ)	s	140	300	230	Willems (2000)
Quantity reservoir constant (k)	s	0.01	20	5	Mannina (2005)
Quality reservoir constant (k_c)	s	0.001	0.01	0.009	Marsili-Libelli & Giusti (2008)
Reoxygenation constant (K_R)	s^{-1}	0.003	0.009	0.005	Marsili-Libelli & Giusti (2008)
Deoxygenation constant (K_D)	s^{-1}	0.001	0.008	0.004	Marsili-Libelli & Giusti (2008)
actual Oxygen production (P_h)	$gO_2 l^{-1} s^{-1}$	0.02	0.05	0.046	Radwan *et al.* (2003)
Respiration (r)	$gO_2 l^{-1} s^{-1}$	0.02	0.05	0.0225	Radwan *et al.* (2003)
Denitrification coefficient (K_{DEN})	d^{-1}	0.1	1	0.5	Radwan *et al.* (2003)
Half saturation constant for the ammonium (K_{s_NH4})	$mgN l^{-1}$	0.01	0.03	0.022	Brown *et al.* (1970)
Nitrogen coefficient (K_N)	d^{-1}	0.54	1.55	1.02	Cox (2003) and Marsili-Libelli & Giusti (2008)
Yield factor describing the amount of oxygen used at nitrification (Y_{Nitr})	mgO_2/mgN	4	4.5	4.47	Brown *et al.* (1970) and Marsili-Libelli & Giusti (2008)

modelling simulation should have to be representative of the model behaviour with respect to the analysis goal. Tr is usually set equal to zero. In the present study, the Nash and Sutcliffe efficiency index was used as the likelihood measure (Nash & Sutcliffe 1970):

$$L\left(\frac{\theta_i}{Y}\right) = \left(\frac{1-\sigma_i^2}{\sigma_0^2}\right) \tag{10}$$

where L (θ_i/Y) is the likelihood measure for the ith model simulation for parameter vector θ_i conditioned on a set of observations Y, σ^2 is the associated error variance for the ith model, and σ_0^2 is the observed variance for the period under consideration. 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. The Nash–Sutcliffe likelihood measure is analytically defined in the range $[-\infty; 1]$, although behavioural simulations are defined in the range [Tr; 1]. The use of the Nash–Sutcliffe efficiency index is recommended by Legates & McCabe (1999) and Moriasi *et al.* (2007), mainly because of its extensive use allowing for comparison with other reports. For similar reasons, values of Pearson's coefficient of determination (R^2) are also calculated, even if they are highly correlated to the Nash–Sutcliffe index and oversensitive to extreme values (Moriasi *et al.* 2007). The R^2 ranges between 0 and 1, where 1 represents a perfect agreement between simulated and observed values and 0 indicates a complete mismatching.

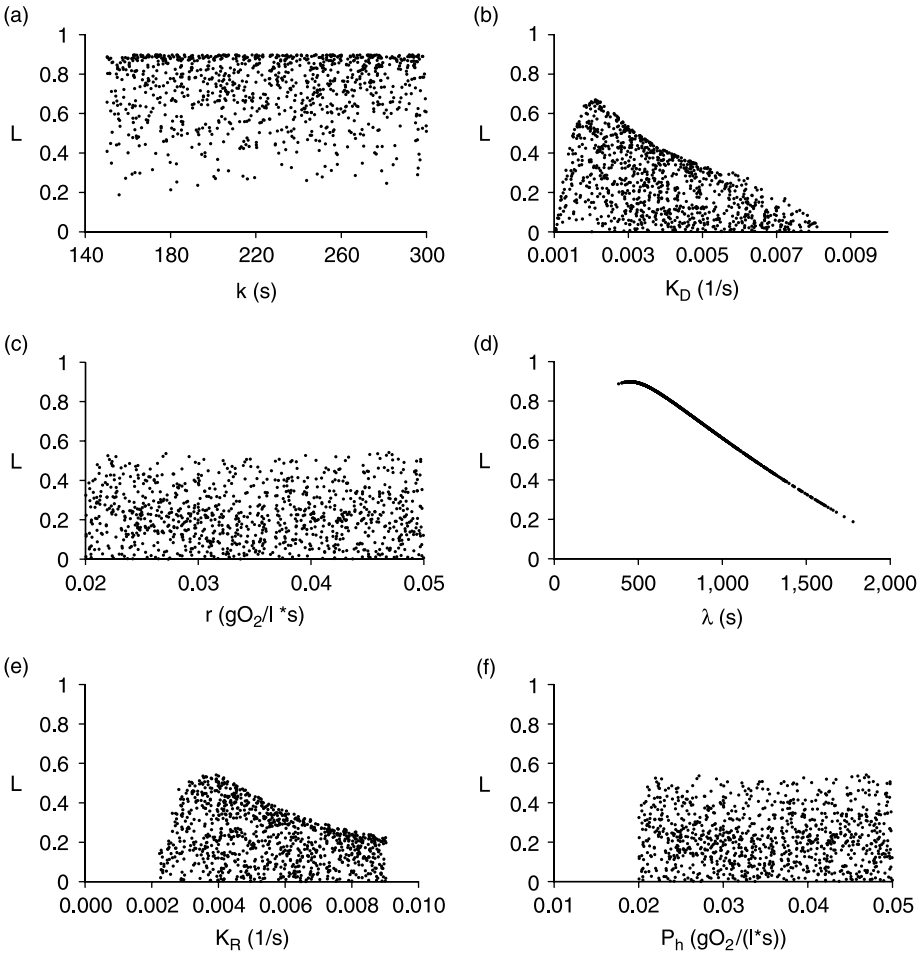

Figure 4 | Scatter plots of some model parameters: Quantity reservoir constant (a), Deoxygenation constant (b), Respiration (c), Lag time (d), Reoxygenation constant (e) and actual Oxygen production d).

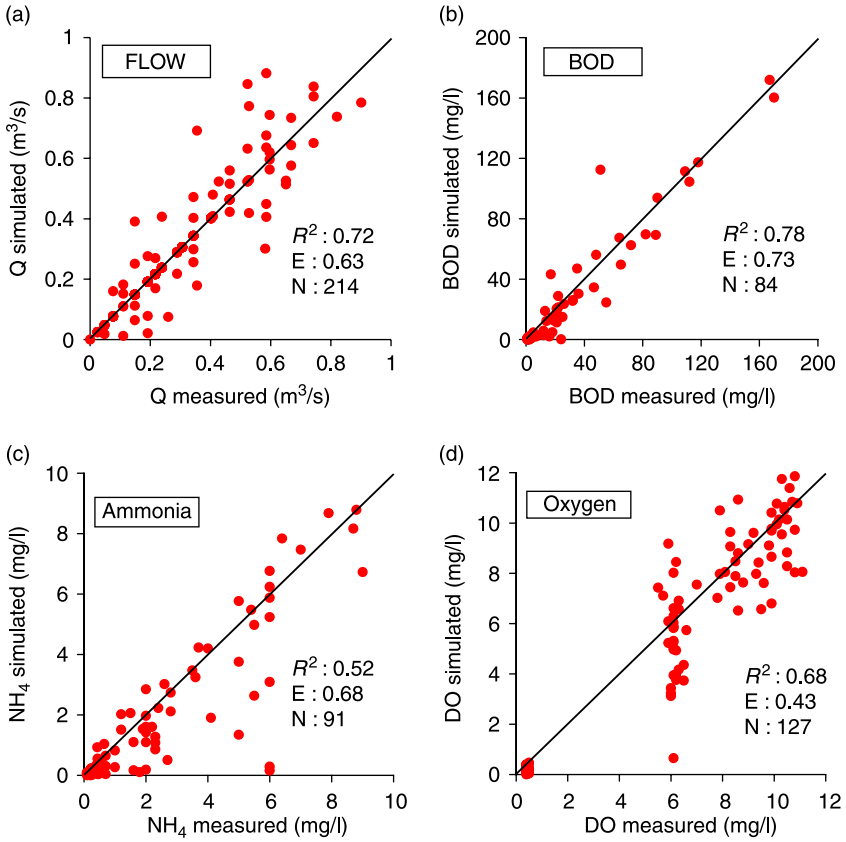

Figure 5 | Comparison of modelled and measured values of: (a), (b), (c), (d), respectively, Q, BOD, NH_4, DO, for the simulated rain events; R^2: Index of Agreement; E: Nash–Suttcliffe-criteria; N: Number of data.

RESULTS AND DISCUSSION

A Monte Carlo procedure was used to generate large numbers of sets of parameters for both sub-models, each parameter value being drawn from ranges (Table 1) thought feasible for the Savena River on the basis of physical argument and previous experience (Brown *et al.* 1970; Willems 2000; Cox 2003; Radwan *et al.* 2003; Marsili-Libelli & Giusti (2008)).

To better pin down the most sensitive model parameters and to evaluate the different roles played by the water quality processes, a preliminary sensitivity analysis was performed. This analysis was carried out generating 10,000 uniform random sets of parameters and using these sets to perform model simulation. As discussed above, for each of these simulations a performance index was evaluated in the form of Nash & Sutcliffe Efficiency Criterion (1970).

Figure 4 shows scatter plots for the likelihood (L) based on the Nash and Sutcliffe index for some of the model parameters. Each dot represents one run of the model with different randomly chosen parameter values within the ranges of Table 1. The generation of the likelihood surface involves a decision on 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 to 1 to calculate the cumulative distribution of the predictive variables.

The most sensitive model parameters are associated with the processes of de-oxygenation and re-aeration. Indeed, Figure 4d shows a strong sensitivity of oxygen to the reaeration coefficient (K_R). Conversely, processes that

are related to the oxygen contribution via photosynthesis are less sensitive (Figure 4f). Such results are in agreement with the physics of the phenomenon. In fact, during storm events, especially for an ephemeral river like the Savena, the major oxygen contribution comes from the reaeration with the atmosphere due to the intense flow turbulence. This aspect is reflected in the reaeration coefficient values. The values of these are orders of magnitude higher than those during dry weather. This aspect confirms the important role played by the flow turbulence during storms.

Figure 5 shows the comparison between measured and simulated values. The model generally shows a satisfactory capability in reproducing the measured values. In terms of the Nash–Sutcliffe efficiency, the model is characterised by different values for the quantity and quality modules. For example, the quantity module efficiency is 0.63 while the quality ones range between 0.43 and 0.73. For quality variables, the modelling results were reasonable (Figure 5), although measured values are slightly biased from simulated ones. Indeed, deviations occurred in the ammonia and oxygen values which can be attributed mainly to the higher complexity of phenomena involved for such variables. Indeed, ammonia and oxygen concentration values are the results of several chemical/physical/biological processes

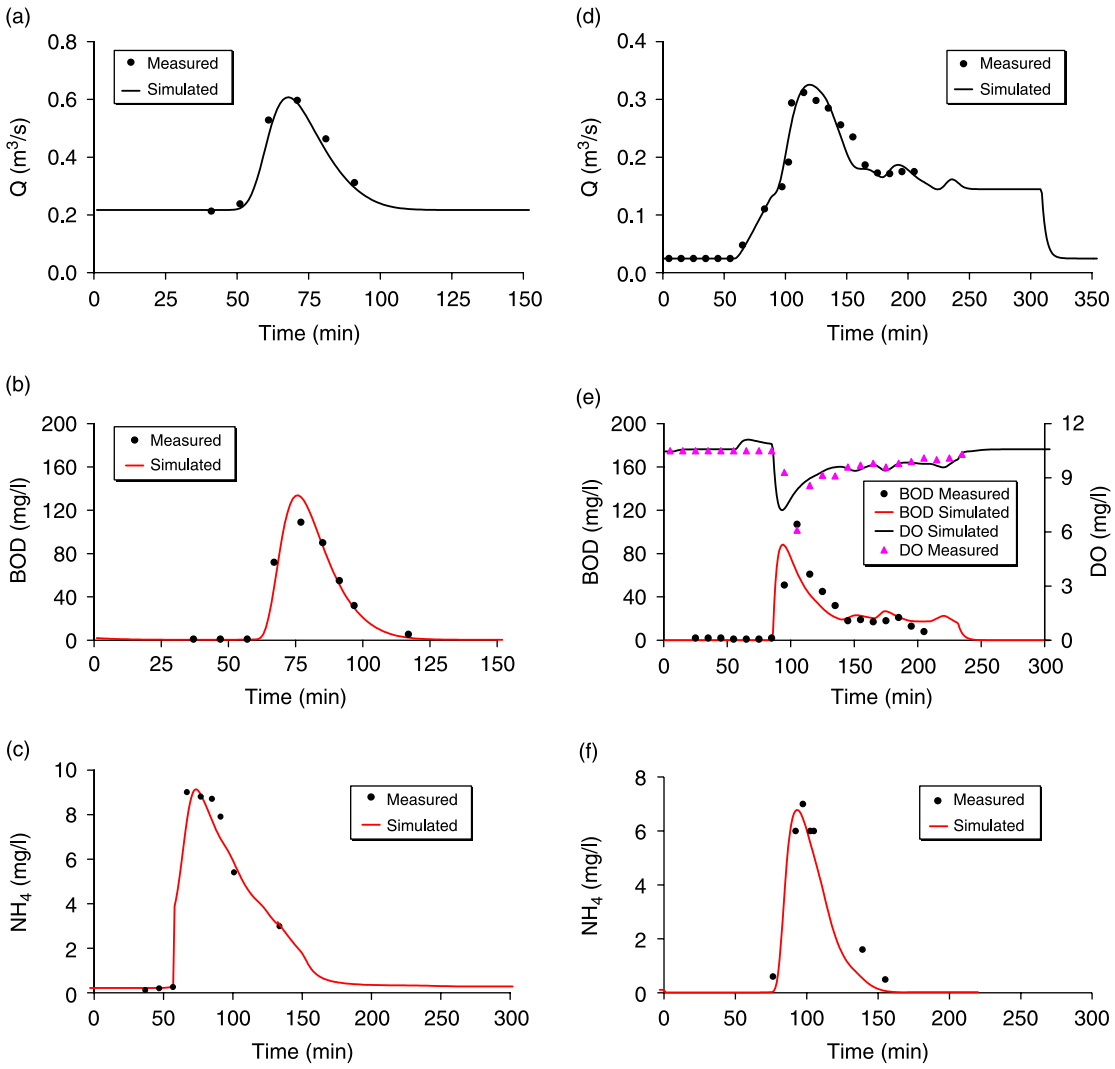

Figure 6 | Model results for the events, respectively, 22/5/98 [(a), (b) and (c)] and 28/11/98 [(d), (e) and (f)].

(i.e. nitrification, denitrification, photosynthesis, atmospheric reaeration, etc.). A slight miscalculation of these processes may contribute to high disagreement between measured and simulated values for ammonia and oxygen concentrations.

In Figure 6 the simulation results are compared to the observations for two events 22/5/1998 and 28/11/1998, respectively, 6a–c and 6d–f. The figures indicate that the overall performance of the model is satisfactory in terms of the magnitude of the concentrations and its variability in time. The model is better at reproducing the hydrographs than the pollutographs (both for BOD, DO and NH_4). In particular, the peaks are not well reproduced, although the model responses can be considered satisfactory. These differences among the sub-models, quantity and quality, are due to the different level of complexity of the system modelled and is likely due to the different measured data uncertainty. Indeed, it is reasonable to suppose that the quality data measured behave with a higher uncertainty level that, of course, influences the modelling process.

The model was very fast computationally, as one simulation takes less than two seconds with a P4 CPU 2.40 GHz PC. Therefore, the proposed model can be considered to be a suitable tool for uncertainty surveys where general several Monte Carlo simulations needs to be run.

CONCLUSIONS

This paper described the development of a parsimonious river water quality model able to evaluate the propagation of pollutants in natural rivers. The model was calibrated and evaluated for the Savena river located in Bologna (IT). The results of the evaluation runs showed that the model was generally able to capture the main features of observed values. *R*-squared values were typically greater than 0.52. Based on the model results the following considerations can be drawn:

- The use of a parsimonious model characterised by reduced data requirements is shown to be a good choice especially in the quite common case of scarce data availability.
- The model showed limited computational time (on the order of seconds for one simulation) and this aspect is relevant for long term simulation needs. This fact is basically due to the CSRS approach that, as shown in previous studies, is faster compared to detailed approaches (Meirlaen *et al.* 2001).
- The model showed a better performance for the quantity than for the quality aspects. Such dissimilar behaviour was justified by the different level of complexity of the system modelled and is likely due to the different measured data uncertainty.
- The sensitivity analysis by means of the GLUE highlighted the deoxigenation and re-oxigenation constants that, during storm events, are the most important parameters for the assessment of river water quality state. Such considerations are particularly important for the case study analysed that is an ephemeral river.
- Reaeration coming from algae activity was negligible, which suggests that such phenomena do not play a relevant role in small rivers during storm events.
- The calibrated model responses and their sensitivity are in good agreement with the observed water quality data, therefore the model is consistent and can be used to generate scenarios as a part of a general strategy to conserve or improve the water quality.

To better assess the model performance, future investigations will examine model application for long-term periods. Moreover, applications to other case studies will also be considered to better generalise some of the conclusions drawn in this research.

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