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The influence of rainfall time resolution for urban water quality modelling

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ABSTRACT

The objective of this paper is the definition of a methodology to evaluate the impact of the temporal resolution of rainfall measurements in urban drainage modelling applications. More specifically the effect of the temporal resolution on urban water quality modelling is detected analysing the uncertainty of the response of rainfall–runoff modelling. Analyses have been carried out using historical rainfall–discharge data collected for the Fossolo catchment (Bologna, Italy). According to the methodology, the historical rainfall data are taken as a reference, and resampled data have been obtained through a rescaling procedure with variable temporal windows. The shape comparison between 'true' and rescaled rainfall data has been carried out using a non-dimensional accuracy index. Monte Carlo simulations have been carried out applying a parsimonious urban water quality model, using the recorded data and the resampled events. The results of the simulations were used to derive the cumulative probabilities of quantity and quality model outputs (peak discharges, flow volume, peak concentrations and pollutant mass) conditioned on the observation according to the GLUE (Generalized Likelihood Uncertainty Estimation) methodology. The results showed that when coarser rainfall information is available, the model calibration process is still efficient even if modelling uncertainty progressively increases especially with regards to water quality aspects.

Key words | GLUE, rainfall temporal resolution, uncertainty assessment, urban stormwater quality modelling

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INTRODUCTION

In urban drainage modelling, rainfall temporal variability can be considered as one of the most critical knowledge elements when dealing with rainfall – runoff model input data. The temporal resolution of rainfall data, usually available for practical applications, is often lower than the one requested for the rainfall-runoff simulation in urban areas, thus compromising model accuracy (Aronica *et al.* 2005). The impact is more relevant on water quality models because the uncertain measurement of rainfall intensity affects both the rainfall-runoff transformation and pollution wash-off modelling thus compounding the level of uncertainty.

Literature studies show that, in urban catchments, where concentration times are often short, the shape, timing and peak of hydrographs are significantly influenced by the time resolution of the rainfall: it has been proved that a too coarse temporal resolution of rainfall data causes a systematic underestimation of peak runoff (Gujer & Krejci 1998). The recommended time resolution of rain data should be such that the rising limb of the resulting runoff hydrograph is divided into three or more time steps (Schilling 1991). Similar considerations can be made for the estimation of the pollutograph derived from wet weather runoff. The temporal resolution of the

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recorded rain data is often lower than the data needed for rainfall-runoff simulations. If the rainfall time series with low resolution are sufficiently long for statistical analyses then different disaggregation procedures have been developed to generate high resolution rainfall time series, e.g. using scaling based or chaotic approaches (Burkhardt-Grammeter & Fankhauser 1998; Sivakumar 2000).

A number of authors have already analyzed the effect of the rainfall time resolution in urban drainage (Zhu & Schilling 1996; Petrovic & Despotovic 1998; Einfalt *et al.* 2002; La Barbera *et al.* 2002; Berne *et al.* 2004). The main aspects that have been addressed are the required recording period for extreme statistics (Cunnane 1973), the effect of the temporal resolution on computed peak runoff (Gujer & Krejci 1998; Aronica & Freni 2005; Aronica *et al.* 2005) and the effect of the spatial resolution of the measurement on the resulting runoff (Schilling 1991; Einfalt *et al.* 1998). However, previous studies on the effect of rainfall resolution on water quality modelling have been rarely detected. Rauch *et al.* (1998) analyzed the effect of uncertainties in the rainfall data for the predictions of integrated urban drainage models. Rauch *et al.* (1998) concluded that the effect of measurement errors is small. Therefore, it seems that the inaccuracy in rainfall measurements and its time resolution do not correspond to an inaccuracy in the model results. In order to gain a confirmation of these results, this paper proposes a methodology for analysing the accuracy and reliability of urban drainage model response by comparing model outputs for rainfall inputs with different temporal resolutions. The methodology is based on a resampling procedure applied to the reference rainfall with the aim of degrading the input data quality. Hyetographs with a coarser temporal resolution were obtained and adopted for model calibration and uncertainty analysis. The impact of rainfall resolution on model performance was analysed by comparing model results with non-dimensional indicator of rainfall data accuracy.

Different temporal windows have been analysed, ranging from two to ten minutes. Two aspects of rainfall have been used to describe data quality: the volume/mass conservation principle and the goodness of rainfall pattern estimation.

The results allowed for quantifying the importance of rainfall information on urban drainage modelling and how this aspect affects the model calibration process thus addressing the operator towards the selection of a minimal temporal resolution to be adopted for rainfall monitoring.

MATERIALS AND METHODS

The urban drainage model

A simplified process model was assembled and has been used representing a good compromise between a highly detailed representation of sewer system (SS) water quality processes and computational parsimony in terms of number of parameters needing calibration (Mannina 2005; Mannina & Viviani 2009; 2010). The model contains two modules: a hydrological and hydraulic module which calculates the hydrographs and a solid transfer module which calculates the pollutographs. The hydrological–hydraulic module starts by calculating the rainfall excess, from the measured hyetograph, using a loss function (which accounts for surface storage and soil infiltration). From the rainfall excess, the model simulates the rainfall-runoff transformation process and the flow propagation with a cascade of one linear reservoir and a linear channel (representing the catchment) and a linear reservoir (representing the sewer network). 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 including their sedimentation and re-suspension.

In order to have a realistic approach to sewer sediment erosion as its transport, particular care has been taken with sediment transformations in sewers, considering their cohesive-like behaviour linked to organic substances and to their physical-chemical changes during transport (Ristenpart 1995). In particular, the transport equation proposed by Parchure & Mehta (1985) coupled to the bed sediment structures hypothesized by Skipworth *et al.* (1999) to simulate the sediment erosion rate was considered. The pollutographs at the outlet of the sewer system have been evaluated by hypothesizing the complex catchment sewer network as a reservoir and by considering the transport capacity of the flow.

Model uncertainty assessment using the GLUE methodology

In order to assess the influence of the rainfall resolution, in the present study the GLUE methodology (Generalized Likelihood Uncertainty Efficiency) has been adopted (Beven & Binley 2006). The GLUE does not require any objective function to be minimised (or maximised), but information regarding the performance of different parameter sets can be derived from indices of goodness-of-fit (likelihood measures). This methodology is attractive because there is no need for detailed distribution functions of the observable variables and of errors when the explicat 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. 2008a; 2008b; 2009a). Similar to other uncertainty analysis methods, the GLUE is based on a large number of Monte Carlo simulations, in which the random sampling of individual parameters from probability distributions is used to determine a set of parameter values. Parameters sets are then compared with respect to their ability to reproduce available observations. Such a comparison is conducted using a likelihood measure. The Nash and Sutcliffe efficiency index (Nash & Sutcliffe 1970) has been used as a likelihood measure in the present study:

$$E = 1 - \frac{\sigma_e^2}{\sigma_o^2} \tag{1}$$

where, σ_e^2 is the variance of errors between observed data and the simulation results and σ_o^2 is the variance of the observations concerning specific variables (i.e. discharges, concentrations, loads, etc.) in a specific section of the system. Parameter sets are thus classified based on the likelihood measure, and sets with poor likelihood weights (with respect to a user-defined threshold Tr) are discarded as non-behavioural. All other sets, θ_i, from behavioural or acceptable simulation runs are retained and their likelihood weights, $E(\theta_i)$, are re-scaled so that their cumulative total sum is equal to 1. The re-scaled likelihood weights, $\ell(\theta_i)$, are obtained according to the following equation:

$$\ell(\theta_i) = \frac{E(\theta_i)}{\sum_{j=1}^{N} E(\theta_j)} \tag{2}$$

where, N is the number of retained behavioural simulations. The GLUE approach considers the distribution of likelihood values to be a probabilistic weighting function for the predicted variables that allows assessment of the uncertainty associated with the predictions, conditioned on the definition of the likelihood function, the input data and the model structure (Gupta et al. 2005).

A method for deriving predictive uncertainty bands of modelling outputs using the likelihood weights from the behavioural simulations was developed by Beven & Binley (2006). In their method, the uncertainty bands are calculated using the 5% and 95% percentiles of the predicted output likelihood weighted distribution. The uncertainty bands must always contain 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 GLUE can be also used for analysing the impact of each parameter on modelling outputs. Plotting the cumulative likelihood distributions for the set of behavioural simulations ($E \geq \mathrm{Tr}$) and the set of non-behavioural simulations ($0 < E < \mathrm{Tr}$), respectively, it is possible, by comparing the deviation between the two, to determine if the model output in question is sensitive to changes in parameter values. If little difference between the two CDFs is found the parameter is considered insensitive with regards to the model output, and on the contrary if a strong difference is present the parameter is considered sensitive. Applying the nonparametric Kolmogorov–Smirnov d-statistic (maximum distance between the two CDFs), a measure of sensitivity is introduced, i.e. $d = 1$ is the most sensitive and $d = 0$ is non-sensitive (Hornberger & Spear 1981; Beven & Freer 2001; Beven et al. 2008). This sensitivity analysis is used to determine the relative importance of each parameter in the model structure. It is evident that the GLUE results can be affected by the definition of parameter variation ranges that can influence the analysis because

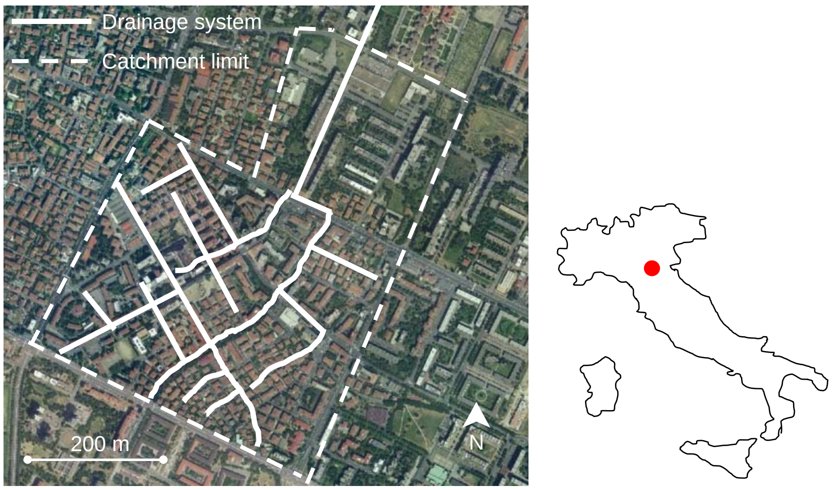

Figure 1 | The Fossolo catchment (Bologna–Italy).

it defines the domain where the model uncertainty is evaluated. The selection of the parameter variation ranges can be accomplished by considering the physical meaning of the parameters, but this approach cannot be used for conceptual parameters that have a weak link to the physical system. In addition, this approach can produce variation intervals that are too wide, thereby leading to the problems described above. To avoid this source of subjectivity, the parameter variation ranges used in this study were estimated by calibration using multiple events (Beven & Binley 2006).

Case study description

The Fossolo experimental catchment is located in the residential area of Bologna (Italy) and it has a combined sewer network which is independent from the surrounding sewer networks (Figure 1). The total drained area is 40.71 ha with an impermeable area of 30.45 ha (74.80%). The buildings in the area are mainly residential with minor service sector businesses. The equivalent number of inhabitants is about 10,000. The catchment has roads with a high vehicle flux (about 40,000 vehicles/day) and other streets with a low vehicle flux (about 1,000 vehicles/day). The final sewer pipe section is polycentric and is 144 cm high and 180 cm wide.

The discharge has been estimated from water depths measured by an ultrasonic probe placed in the main channel matched with the discharge rating curve for the same channel. A refrigerated automatic sampler with 24 bottles, each with one litre volume, has been used. For each sample BOD, COD and TSS concentrations have been evaluated. 12 events have been measured for both quantity and quality (Table 1). The field campaign has been carried out by Bologna University (Artina *et al.* 1997; Maglionico 1998). More details about the case study can be found in previous literature (Artina *et al.* 1997; Freni *et al.* 2008*a*; Mannina & Viviani 2010).

Table 1 | Characteristics of 12 rain events used in the application

	Total rainfall (mm)	Max intensity (mm/h)	Duration (min)	ADWP (h)
Minimum	2.8	12	45	50
Maximum	72.2	147	921	402
Mean	18.9	45	258	167

METHODOLOGY APPLICATION

As discussed in the introduction, the aim of this study was to analyse the uncertainty of the urban drainage model response, within the GLUE framework (Beven & Binley 2006), when rainfall inputs of different temporal resolutions are used. Twelve fully monitored rainfall events have been used for the analysis of modelling response to rainfall temporal resolution. A resampling procedure has been applied to the reference rainfall to degrade the available information and to obtain hyetographs with a coarser temporal resolution. The rainfall duration has been divided into a number of constant time intervals, and for each of these temporal windows the average intensity has been evaluated. Different temporal windows have been analysed, namely two to ten minutes at one minute steps. The historical rainfall data (one minute time resolution) have been taken as the reference rainfall. The resampling procedure has been applied to the reference rainfall to obtain hyetographs with a coarser temporal resolution; in this way, the impact of rainfall temporal resolution on modelling performance has been integrated in the general framework of mathematical modelling uncertainty. The model time step has been set constant and equal to one minute for all rainfall time resolution scenarios.

Two aspects of rainfall have been used to describe data quality: the volume/mass conservation principle and the goodness of rainfall pattern estimation. The volume balance is guaranteed by the use of a conservative resampling process. In order to evaluate the dependencies between model performance and accuracy of the description of a rainfall event, a resampling accuracy index (RAI) has been computed, applying the Nash – Sutcliffe criterion (1970) between resampled rainfall series and the real event (Andreassian *et al.* 2001; Aronica & Freni 2005). The RAI value for the real event is obviously equal to 1, and decreases depending on the approximation of the resampled event. The RAI has been evaluated as follows:

$$\mathrm{RAI} = 1 - \frac{s_e^2}{s_o^2} \qquad (3)$$

where s_e^2 is the variance of errors between the real and rescaled rainfall and s_o^2 is the variance of observed rainfall.

The GLUE uncertainty analysis has been carried out for all the analysed rainfall cases according to the following steps.

- Initially, in order to reduce the number of analysed parameters, a preliminary sensitivity analysis has been carried out prior to the model uncertainty analysis. Following this preliminary model parameter analysis, the number of model parameters was reduced from 17 to 11 (5 for the quantity sub-model and 6 for the quality sub-model). Details of this rationalization of model parameters are discussed in Mannina (2005), Freni *et al.* (2009*b*) and Mannina & Viviani (2010).
- The uncertainty analysis has been carried out separately on the water quantity sub-model (varying the 5 sensitive parameters) and then on the water quality sub-model (varying the 6 remaining parameters) and fixing water quantity parameters to calibration values. Uniform prior distributions have been considered for all the analysed parameters. The acceptability threshold has been set to 0.4 for quantity parameters and 0.3 for quality one and Monte Carlo runs were stopped once 5000 behavioural simulations were obtained. As pointed out in Freni *et al.* (2008*b*) the threshold is user-defined and its selection should be based on user's confidence in the model and on available computational resources. In the present case, two different thresholds were selected both considering the expected higher uncertainty of quality modules and their higher computational cost, suggesting to reduce the ratio between non-behavioural simulations and total model runs.
- The uncertainty bands have been constructed for four model outputs (SS outflow peak and volume; the SS output TSS peak concentration and mass. The construction of parameters cumulative likelihood distributions has been based on the aforementioned behavioural simulations and on 5000 non-behavioural one.

RESULTS ANALYSIS

Analysis results will be discussed by means of two of the twelve analysed events having a simple peaked structure (event 06/08/97) and a multi-peaked and complex pattern (event 28/10/94). Figures 2 and 3 show the real (one minute time resolution) and rescaled rainfall events (from two up to ten minutes time resolutions). Such interval was selected following the literature considerations discussed in the introduction and considering that Fossolo catchment is characterised by concentration times between 20 and 30 min. Ex-post evaluations (after calibrating the model with coarse temporal resolutions) showed that water quality model performance drops rapidly if temporal resolutions higher than 10 min are adopted.

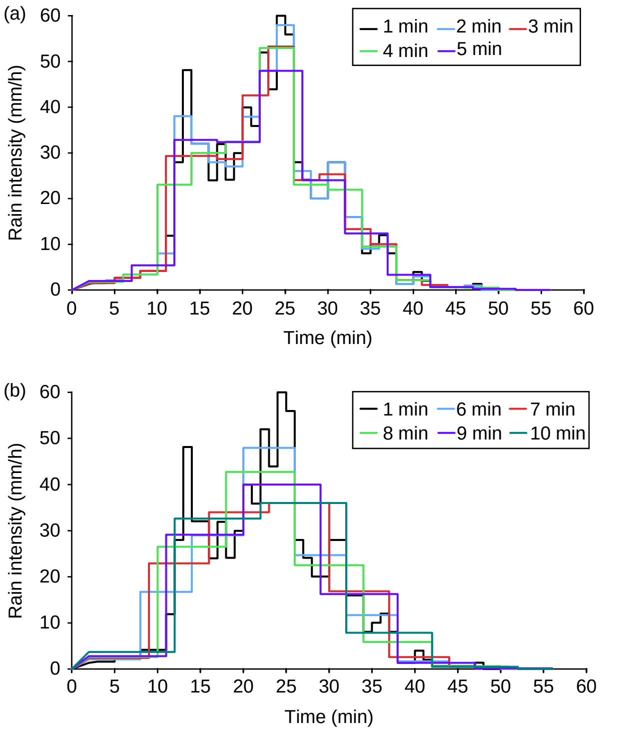

Figure 2 | Event 6/8/97—real and resampled events reported in terms of rainfall intensities considering different resolutions (a) 1–5 min and (b) 6–10 min.

Table 2 shows the RAI values for the two analysed events: the single peaked event is characterised by higher RAI values demonstrating that the impact of time resolution reduction is lower; the multi-peaked event is characterised by lower RAI values thus showing that the rainfall complexity is compromised when rainfall resolution is reduced.

Figures 4 and 5 show the uncertainty bands computed on SS outflow peak discharge, the SS outflow volume, the TSS peak concentration and the TSS mass discharged at the end of the event. For the event 08/06/97 the analysis of water quality sub-model was interrupted after the rainfall temporal resolution reached six minutes because the analysis did not provide behavioural simulations.

Figures 4 and 5 allow for some interesting considerations:

- The model is able to obtain a good calibration both for the quantity and for the quality sub-models, even with coarser rainfall time resolutions. Small calibration errors for the quality sub-models are obtained only for rainfall time steps higher than 6 min (Figure 4c–d). These results are consistent with previous studies (Rauch *et al.* 1998) and they are likely due to the fact that the modelled processes are highly over-parameterized (Mannina 2005; Freni *et al.* 2008*b*; Willems 2008). This fact leads to compensation ability of the model parameters with respect to the impact of coarser rainfall resolution information. The impact of rainfall resolution on model results is consistent with previous studies (Thorndahl *et al.* 2008). In particular Thorndahl *et al.* (2008) compared the results of model outputs using rainfall recording from a single local rain gauge and an area averaged input from two rain gauges. The authors noted that extreme values are scarcely influenced by the accuracy of rainfall. More specifically, Thorndahl *et al.* (2008) showed that of the estimation of extreme values (i.e maxima water levels and combined sewer overflow volumes) of a detailed urban drainage model is not improved using more complex rainfall input.
- The impact of rainfall resolution on water quality aspects is higher than the impact on quantity aspects in terms of peak discharge and outflow volume. This may be due to larger equifinality among water quality parameters with

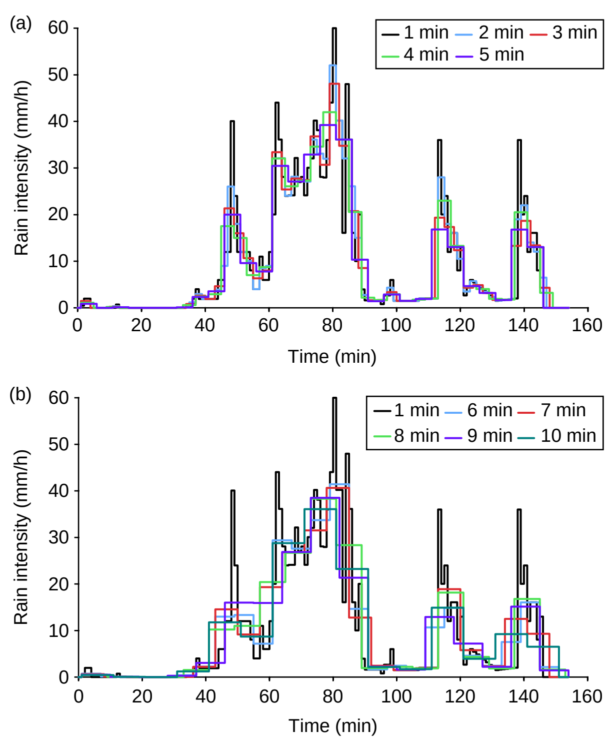

Figure 3 | Event 28/10/94—real and resampled events reported in terms of rainfall intensities considering different resolutions (a) 1–5 min and (b) 6–10 min.

Table 2 | The RAI values for the real and rescaled events

	Rainfall time resolution [min]									
Event	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
06/08/1997	1.000	0.978	0.943	0.935	0.883	0.858	0.845	0.847	0.831	0.826
28/10/1994	1.000	0.893	0.842	0.848	0.822	0.771	0.742	0.751	0.697	0.689

respect to the quantity ones. The equifinality property makes several model parameters sets to behave equally with respect to model outputs thus increasing uncertainty (Beven & Freer 2001).

- Uncertainty bands are progressively wider showing that the coarser of rainfall information increases the modelling uncertainty; such effect is more evident for the event 28/10/94 that is characterised by lower RAI values.

Figure 6 shows cumulated likelihoods obtained from behavioural and non – behavioural simulations for different rainfall time resolutions and for the catchment runoff coefficient Φ. The model is sensitive to the parameter and a translation of the calibrated value is evident from smaller temporal resolutions to higher ones. The Komogorov – Smirnov statistic d is not greatly affected by rainfall temporal resolution thus demonstrating that the relative importance of parameters on modelling outputs is not affected by input rainfall level of information.

Figure 7 shows the relationship between RAI values and the relative uncertainty band width for the four analysed model outputs. The uncertainty band relative width is obtained dividing the uncertainty band width by its value at the maximum rainfall resolution. For this reason,

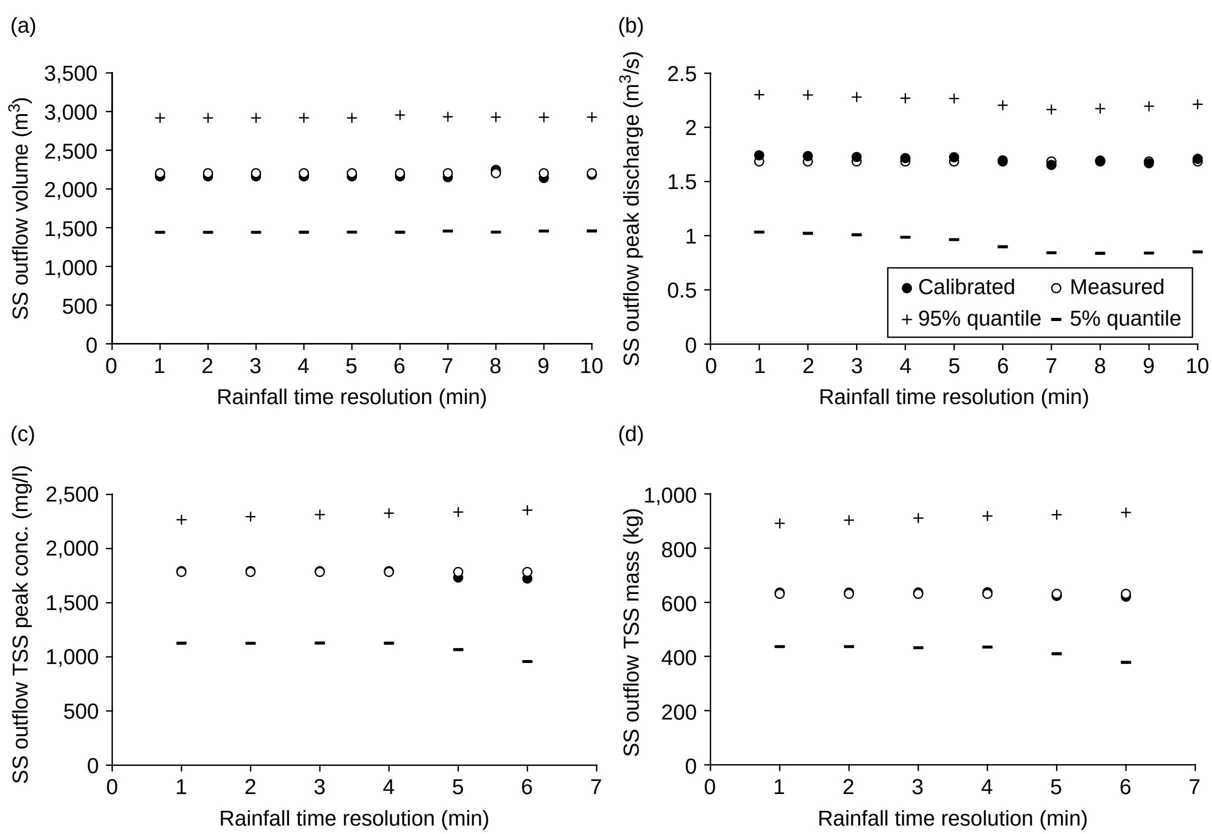

Figure 4 | Uncertainty bands obtained for the event 6/8/1997.

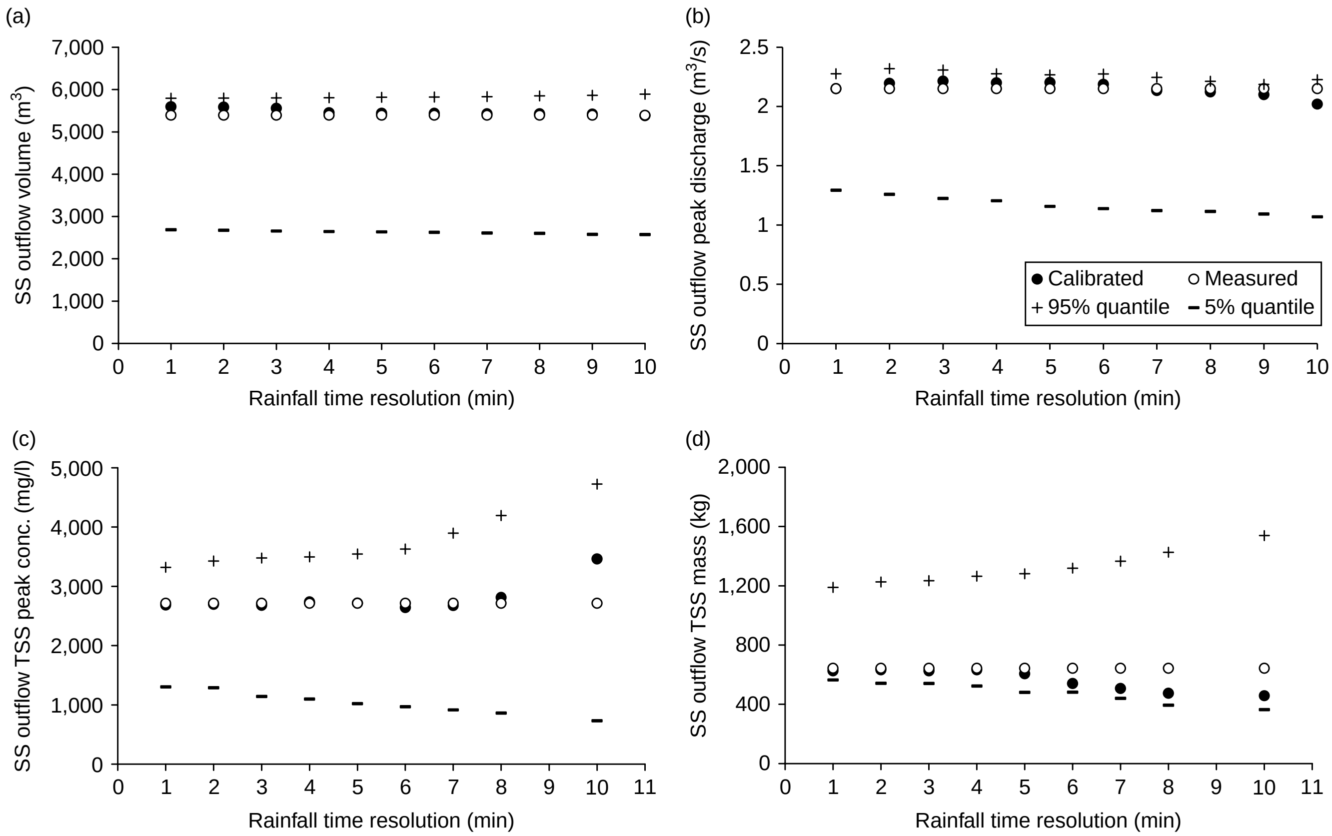

Figure 5 | Uncertainty band obtained for the event 28/10/1994.

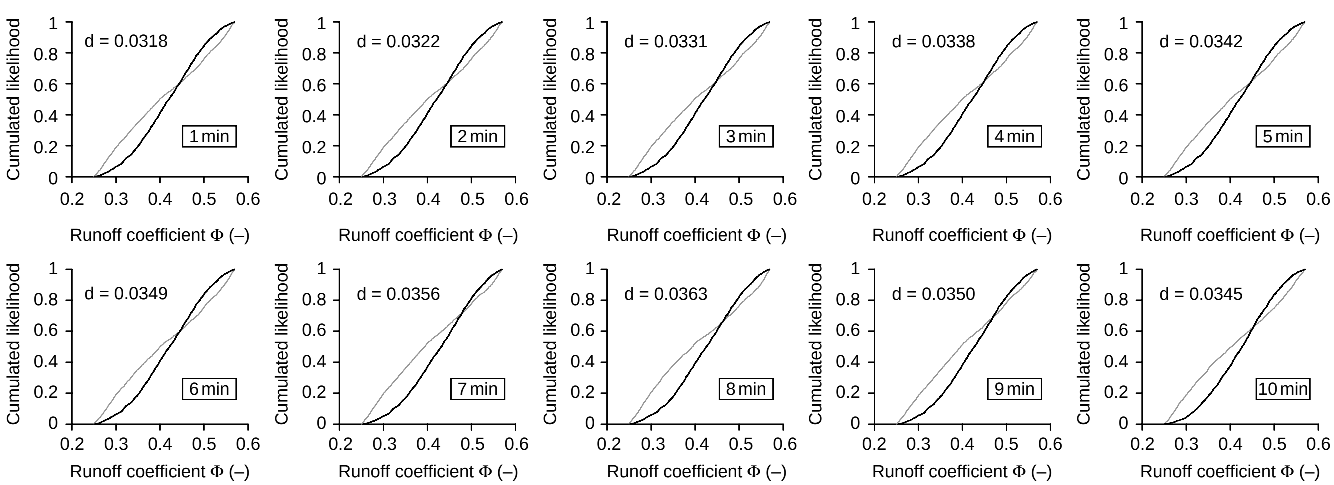

Figure 6 | Cumulated likelihood for TSS obtained for different rainfall temporal resolutions for the catchment runoff coefficient Φ.

if the uncertainty band relative width is higher than one while RAI is reducing, the uncertainty increases with the degradation of rainfall information.

Figure 7 shows that for both the analysed events the relationship between RAI and uncertainty band relative width is sensibly linear and superimposed for water quantity modelling outputs and it is sensibly more than linear for quality aspects: the degradation of rainfall information equivalent to a RAI value equal to 0.7 doubles the uncertainty band width.

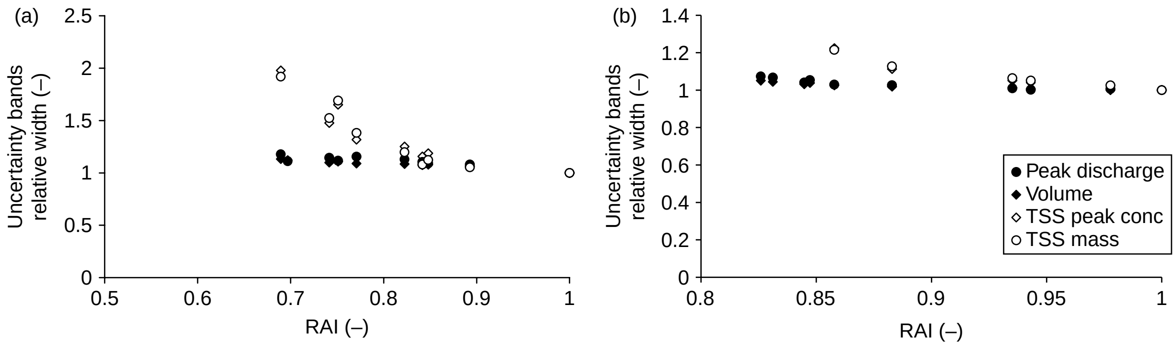

Figure 7 | Comparison between RAI and uncertainty band relative width for the events: (a), 28/10/1994 and (b), 6/8/1997.

CONCLUSIONS

The present paper proposed a methodology for evaluating the impact of imperfect rainfall knowledge on urban drainage water quality modelling. The methodology is based on the comparison of rainfall information level (evaluated by means of a non-dimensional accuracy index) and model performance (based on the evaluation of calibration performance and uncertainty bands).

The complexity of modelling approaches and the lack of data are effectively the most relevant sources of uncertainty in urban water quality assessments. The response of an urban water quality home-made model has been assessed in terms of modelling uncertainty for different scenarios obtained by progressively increasing the time step of available rainfall data.

The analysis showed that water quantity sub-models are less affected by rainfall data temporal resolution. Water quality sub-models are more sensitive to rainfall data characteristics probably due to the high sensitivity of wash–off algorithms to rainfall intensity. Such higher impacts are demonstrated by the increase of the uncertainty band width with respect to water quantity sub-models. Nevertheless, when coarser rainfall information is available, the model calibration process is still efficient and good results can be obtained even assuming rainfall data time steps between seven and ten minutes. In these cases, model parameters compensate for the degraded rainfall information in order to match modelling outputs with measures. In these cases, the physical significance of parameters may be lost. The use of synthetic indices, such as RAI, can provide an understanding of the link between modelling uncertainty, rainfall characteristics and rainfall time steps. With this regard, the paper highlighted a good correlation between the RAI and uncertainty band widths of water quantity and water quality results.

This study is an important step in defining methodologies for evaluating the impact of rainfall temporal resolution on uncertainty in water quality modelling. Nonetheless, the analysed case is very specific and more modelling examples and research is required before generalisations can be made. Also the influence of database extension is a point to be better analysed in the future even if small datasets are quite frequent in water quality modelling and such condition increases the impact of model over-parameterization increasing its versatility but adding higher uncertainty to its responses.

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