Bayesian inference analysis of the uncertainty linked to the evaluation of potential flood damage in urban areas

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ABSTRACT

Flood damage in urbanized watersheds may be assessed by combining the flood depth–damage curves and the outputs of urban flood models. The complexity of the physical processes that must be simulated and the limited amount of data available for model calibration may lead to high uncertainty in the model results and consequently in damage estimation. Moreover depth–damage functions are usually affected by significant uncertainty related to the collected data and to the simplified structure of the regression law that is used. The present paper carries out the analysis of the uncertainty connected to the flood damage estimate obtained combining the use of hydraulic models and depth–damage curves. A Bayesian inference analysis was proposed along with a probabilistic approach for the parameters estimating. The analysis demonstrated that the Bayesian approach is very effective considering that the available databases are usually short.

Key words | Bayesian uncertainty analysis, flooding damage, urban drainage modelling, urban flooding

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INTRODUCTION

Local flooding is a recurrent problem for many urban areas in the world. Flood impact can be very high because urban areas are densely populated and contain essential infrastructures: even a small-scale flood event could cause considerable damage and urbanisation in flood-prone areas increases the hydraulic risk. Moreover, the frequency and the magnitude of flooding damage may rise in the future as consequence of the climate change (EEA *et al.* 2008). For a given frequency, the evaluation of the potential flood damage in a urban watershed is an essential prerequisite to support decision makers in planning reliable measures for flooding mitigation and/or prevention.

In the last decades, several procedures have been developed for quantifying the expected flood damage in a urban watershed: some methodologies are based on a-priori estimation of the potential damage and are founded on the value of exposed goods (Oliveri & Santoro 2000); others propose the interpolation of the real damage data recorded during historical flooding events (Meyer & Messner 2006; Nascimento *et al.* 2006; Freni *et al.* 2010a). The expected flood damage is more often evaluated by means of depth–damage functions (Apel *et al.* 2006; Dawson *et al.* 2008; de Moel and Aerts 2011) that usually express the total economic damage on public and private properties (e.g., buildings, cars, roads) as a function of inundation depth. Depth–damage functions are usually obtained from systematically applied survey procedures, but they can also be derived from the analysis of insurance claims or historical flood data. They should be strictly applied for the analysis of the urban watershed for the data collected even if, in practical applications, the extrapolation to similar urban areas is a common practice (Apel *et al.* 2006). The application of advanced hydraulic models, able to simulate flooding volume propagation, may be useful allowing the extrapolation of the available data both in time (simulating flooding events for which damage data are not available) and in space (transferring the analysis to un-gauged urban areas).

Several procedures propose assessing flood damage in urbanized watersheds by combining the flood depth–damage curves and the outputs of urban flood models (Jonkman *et al.* 2008; Prince & Vojinovic 2008; Freni *et al.* 2010a). However, hydraulic models only permit a conceptualised representation of the real drainage system and of the physical processes occurring during surface flooding propagation (Beven & Binley 1992; Aronica *et al.* 2005; Gupta

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et al. 2005; Fontanazza *et al.* 2011). Even if hydraulic models have been recently improved for simulating flood propagation in urban watersheds, the complexity of the physical processes that must be simulated and the limited amount of data available for model calibration may lead to high uncertainty in model results (Leandro *et al.* 2009; Lipime-Kouyi *et al.* 2009; Maksimović *et al.* 2009).

Depth–damage functions are also affected by significant uncertainty related to the simplified structure of the regression law adopted and to the reliability of the collected data: flooding data can be affected by measurement errors and they are often spatially aggregated because parts of the system are not accessible during flooding (Freni *et al.* 2006). As consequence, flood damage predictions are usually affected by a degree of intrinsic uncertainty that cannot be realistically removed (Dotto *et al.* 2009). The investigation of the sources and magnitude of the uncertainty related to flood damage assessment is needed to provide a useful tool for flooding mitigation planning. Decision makers can use such analysis in order to acquire additional knowledge aimed at better understanding potential flood processes and damage (Manson *et al.* 2002).

The present paper investigated the uncertainty in flood-damage evaluation related to the use of both hydraulic models and depth–damage curves. An uncertainty evaluation method based on a Bayesian inference analysis was proposed along with a probabilistic approach to model parameter estimation. Flooding data are collected on a recursive basis, event after event: each time new data become available, the flooding database can be updated increasing its dimension and allowing for potential reduction of uncertainty. This procedure fits perfectly with the Bayesian paradigm that is able to update uncertainty estimation and parameter probability distributions once new information is added to the model. For this reason a Bayesian approach was chosen. The implementation of a Bayesian statistical approach helps to evaluate the statistical confidence intervals that represent the uncertainty linked to the estimation of flooding damage. Unfortunately, the application of Bayesian analysis relies on initial subjective hypotheses that may affect the final results requiring preliminary verification (Freni *et al.* 2010b). Therefore, the objectives of the present paper were:

- to evaluate the robustness of the Bayesian approach in terms of progressive reduction of uncertainty once new data become available;
- to investigate the impact of initial subjective user assumptions on the reliability of the analysis.

The analysis was applied to a real case study: the 'Centro Storico' watershed of the city of Palermo (Italy), a highly urbanized area affected by local surface flooding due to the drainage system insufficiency that even occurs for high-frequency rainfalls.

MATERIALS AND METHODS

The Bayesian inference analysis

The analysis and the evaluation of the uncertainty involved in urban drainage modelling has recently attracted the attention of researchers (Willems 2008; Kleidorfer *et al.* 2009). Several approaches have been developed to deal with parameter and modelling uncertainty adopting classical Bayesian probability theory. This theory is known to have a strong theoretical basis and to provide a unified approach compared with those statistical and deterministic methods (Howson & Urbach 1991).

The Bayesian techniques (Kuczera & Parent 1998; Kavetski *et al.* 2006a, b) allow for both parameter estimation and uncertainty analysis by providing a posterior distributions for parameter values in that the true value should be enclosed. In the present paper, the Bayesian approach was applied to analyse of both the uncertainty related to hydraulic model parameters and to the depth–damage curve coefficients.

The Bayesian method relies on the assessment of uncertainty in the model parameters in terms of probability. The uncertainty of a generic model parameter, θ, is evaluated from a prior probability distribution, $P(\theta)$, that represents the inference on, θ, based on historical data or the expert prior opinion about the possible true values of θ, before looking at new data (Freni *et al.* 2010b). This prior information is updated by means of new observed values, D, to obtain the posterior information according to the Bayes' theorem (Bayes 1763), which can be expressed as:

$$P(\theta|D) = \frac{P(D|\theta)P(\theta)}{\int P(D|\theta)P(\theta)d\theta} \tag{1}$$

where is $P(\theta|D)$ the posterior distribution of the parameter θ, $P(\theta)$ is the prior knowledge of the conditional probability for the measured data, and $P(D|\theta)$ is the *likelihood function* of the model. The *likelihood function* can be written in the multiplicative form by imposing that the residuals between the modelled and observed values are distributed according to a normal distribution with null average and variance σ_e^2:

$$P(D|\theta) = \prod_{i=1}^{m} \frac{1}{\sqrt{2\pi\sigma_e^2}} \exp\left(\frac{(D_i - Y_i)^2}{-2\sigma_e^2}\right) \tag{2}$$

where Y_i is the modelling response corresponding to the m-th available measure D_i of a certain variable (i.e. flooding depth, volumes, damage, etc.) at a specific system area.

The posterior distribution (Equation (1)) describes the uncertainty of θ after observing the new data, D (Fernandes *et al.* 2010). Posterior distributions are populated by running Monte Carlo simulations using parameter values randomly drawn from prior distributions. The formulation of a likelihood function and the definition of the prior probability distribution are two crucial choices of this method made in subjective way. The former has to be related to the hypothesis made about the distribution of residuals between modelled and observed values. A common practice assumes that residuals are normally distributed (Willems 2008; Freni *et al.* 2010b). In this paper, a Box-Cox transformation (Box & Cox 1964, 1982) was used to ensure this hypothesis because the results of Bayesian inference may be unreliable if the residuals are distributed in a different way (Yang *et al.* 2008). Furthermore, Bayesian approaches may not be objective if the choice of prior parameter distributions are not made on physical observations. In the present paper, prior parameter distributions were set to be uniform because no prior knowledge was initially considered.

The effectiveness of Bayesian approach in reducing uncertainty when new data become available was tested dividing the existing database in three equal parts in order to carry out three subsequent Bayesian updates simulating the acquisition of new data once new flooding events happen. The analysis of uncertainty affecting depth–damage was based on a previous study and here simply transferred in order to focus the attention on the reliability of the Bayesian approach (Freni *et al.* 2010a).

The mathematical model

In the last years, mathematical models have been improved in order to provide reliable tools for estimating flood volumes, depths, velocities on catchment surface, and the resultant effects of a flood on the inhabitants (Hsu *et al.* 2000; Merz *et al.* 2004; Ettrich *et al.* 2005; Schmitt *et al.* 2005; Carr & Smith 2006; Chen *et al.* 2007; Hunter *et al.* 2008; Leandro *et al.* 2009). In the present paper, an urban drainage model based on the SWMM application (Huber & Dickinson 1988) was adopted to simulate urban drainage-system behaviour. A distributed 'non-linear reservoir' model was used to simulate surface runoff and take into account both surface storage and infiltration (Rossman 2009). A dual drainage approach was employed to simulate surface flood propagation (Djorgević *et al.* 1999; Leandro *et al.* 2009) where underground and surface drainage systems (streets, pedestrian lawns, etc.) are schematised in a unique network made by two sets of channels that are dynamically interconnected by sewer manholes. Flow into underground pipes and surface channels were simulated by solving the complete 1-D De Saint Venant (DSV) equations. Flood velocity and surface backwater propagation were analysed by means of complete DSV equations. Details about the adopted model can be found in Freni *et al.* (2010a). This approach can be used to examine a wide range of problems: from frequent and limited local flooding to global system surcharge with high discharges and water levels on streets. Table 1 shows the variation range of the model parameters for which the prior uniform distribution was applied. The variation range of each parameter was fixed from the calibration values obtained in previous application of the model to the same case study (Fontanazza *et al.* 2011).

The case study

The 'Centro Storico' catchment of the city of Palermo (Italy) is the oldest part of the city and it is strongly urbanized (Figure 1). The urban catchment is about 2.5 km^2 with about 88% of impervious areas, mainly buildings, roads and squares, and with few pervious areas, mostly

Table 1 | Variation range and unit of measure of each parameter

Parameters	M.U.	Min.	Max.
Impervious area surface storage	mm	0.5	2.0
Pervious area surface storage	mm	3.5	8.5
Impervious area Manning's roughness	–	0.020	0.033
Pervious area Manning's roughness	–	0.025	0.050
Max infiltration rate (Horton)	mm/h	62.0	117.2
Saturated soil infiltration rate (Horton)	mm/h	12.2	22.7
Underground drainage system Manning's roughness	–	0.014	0.025
Surface channels Manning's roughness	–	0.021	0.034

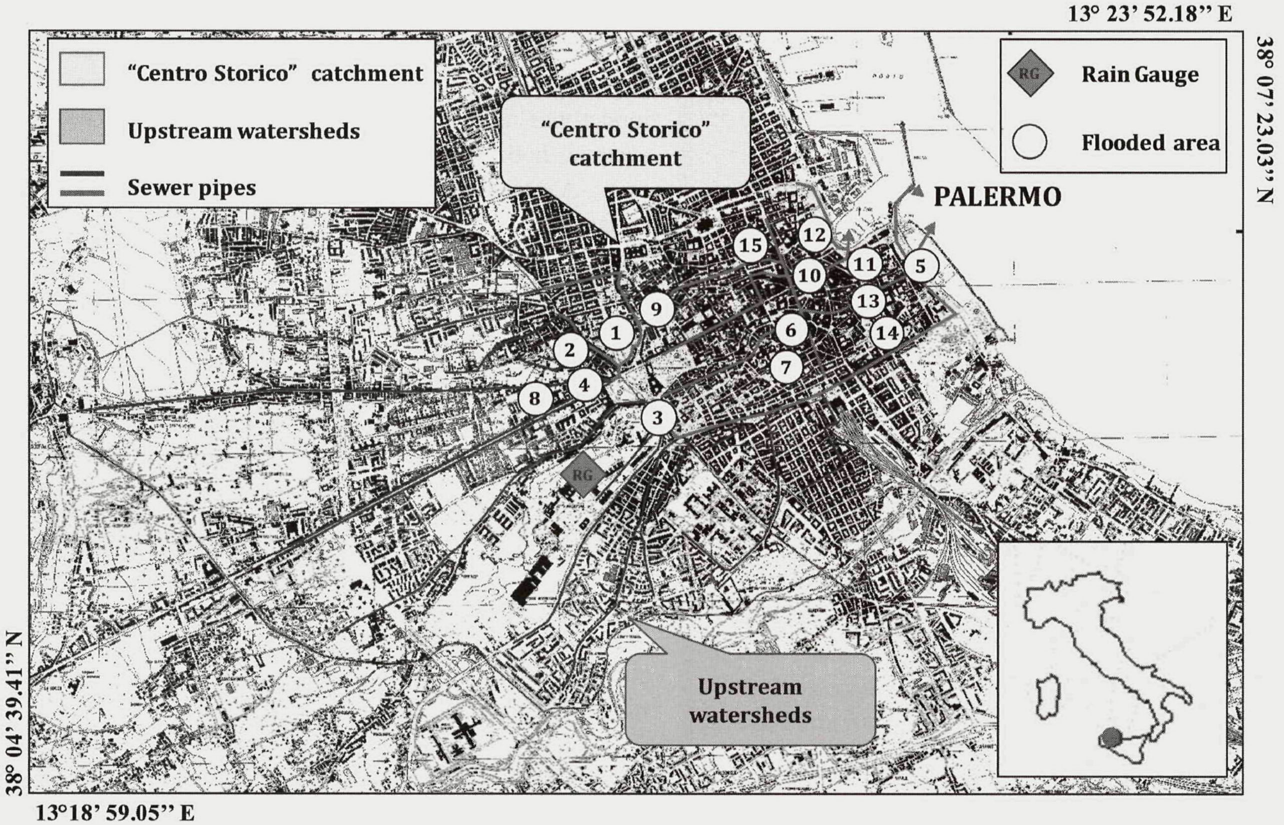

Figure 1 | The 'Centro Storico' catchment, with flooded areas.

fragmented into public parks and many courtyards in mansion and religious buildings spread along the main roads. The most common land uses are residential dwellings. Many monuments and other estates having a cultural or artistic significance (theatres, churches, monasteries, etc.) were erected in this area that is one of the largest historical city centre in Europe. The whole catchment is drained by a very old sewer system of about 118 years in age and with a total length of about 56 km. It receives both storm and waste water from the upstream less urbanized watersheds as well. Local surface flooding due to the system insufficiency often occur even for high-frequency rainfalls. More than 40 flooding events affected several areas of the watershed from the 1993 to the 2008 (Figure 1). The historical rainfall events causing flooding were recorded by the Parco d'Orléans rain gauge (RG), located in this area and operative with a temporal resolution of 1 minute since 1993.

A wide database of flooded areas, water depths and volumes, durations and damaged properties was collected by querying fire brigades and insurance companies (Freni *et al.* 2010a): fire brigades report details on each flooded area including information on flooded properties, aerial extension and volume of flooding, possible cause of flooding (surface runoff, drainage surcharge, pipe failure, etc.); insurance companies, on the other hand, match flooded property data with requested and delivered compensation. Table 2 shows the values of mean water depths and flooding frequencies.

Table 2 | Frequency and mean flooding depth at different locations in the analysed catchment

Flooded area	Mean flooding depth [cm]	Average return period [yrs]	Flooded area	Mean flooding depth [cm]	Average return period [yrs]
1	145.71	0.54	9	42.89	0.56
2	61.16	0.56	10	19.27	0.71
3	39.96	0.68	11	27.72	0.56
4	44.21	0.56	12	53.18	0.54
5	57.82	0.56	13	42.18	0.54
6	31.00	0.56	14	32.07	0.56
7	23.21	0.68	15	23.62	1.50
8	45.27	0.59			

The available historical flood data were divided in three subsets of equal consistency (14 flooding events for each group) in order to run three different Bayesian calibration and uncertainty analysis phases (Jin *et al.* 2010): the first subset contains flooding data collected from January 1994 to April 1999; the second from May 1999 to January 2003; and the third from February 2003 to the end of 2008. The first and the second subsets were used for the assessment of the prior knowledge when the second and the third subsets were analysed, respectively.

METHODOLOGY APPLICATION AND RESULTS ANALYSIS

The aim of the analysis was the evaluation of the capability of the Bayesian method to provide an initial reliable judgment on the acceptability of the model, even if available data are scarce, and to evaluate the reduction in uncertainty once new data becomes available.

Starting from the prior uniform knowledge about parameters, the first Bayesian uncertainty analysis was carried out on the first data subset. Posterior parameter distributions and expected damage uncertainty were obtained by 1.000 Monte Carlo Simulations (MCSs) in which random parameter sets, extracted from prior distributions, were used to simulate flooding propagation for all the events of the subset. The results of the model were used to estimate flooding damage in all the 15 flooded areas of the case study according to the procedure described in Freni *et al.* (2010a). The total damage was estimated for all MCSs in order to evaluate the likelihood function (Equation (2)). The consequent posterior parameter distribution was obtained by applying Equation (1).

Uncertainty bands around the total measured damage were obtained by ranking the simulated damage values, provided by MCSs, with regard to the likelihood function $P(D|\theta)$ and selecting the 5% and the 95% quantiles. If the measured damage values are included in the band, the adopted modelling approach can be accepted and the width of the band can be considered as the magnitude of uncertainty related to damage estimation.

Figure 2 shows the uncertainty band of expected damage after the Bayesian update based on the first data subset and the posterior distributions of the two most influential hydraulic parameters (impervious area Manning's

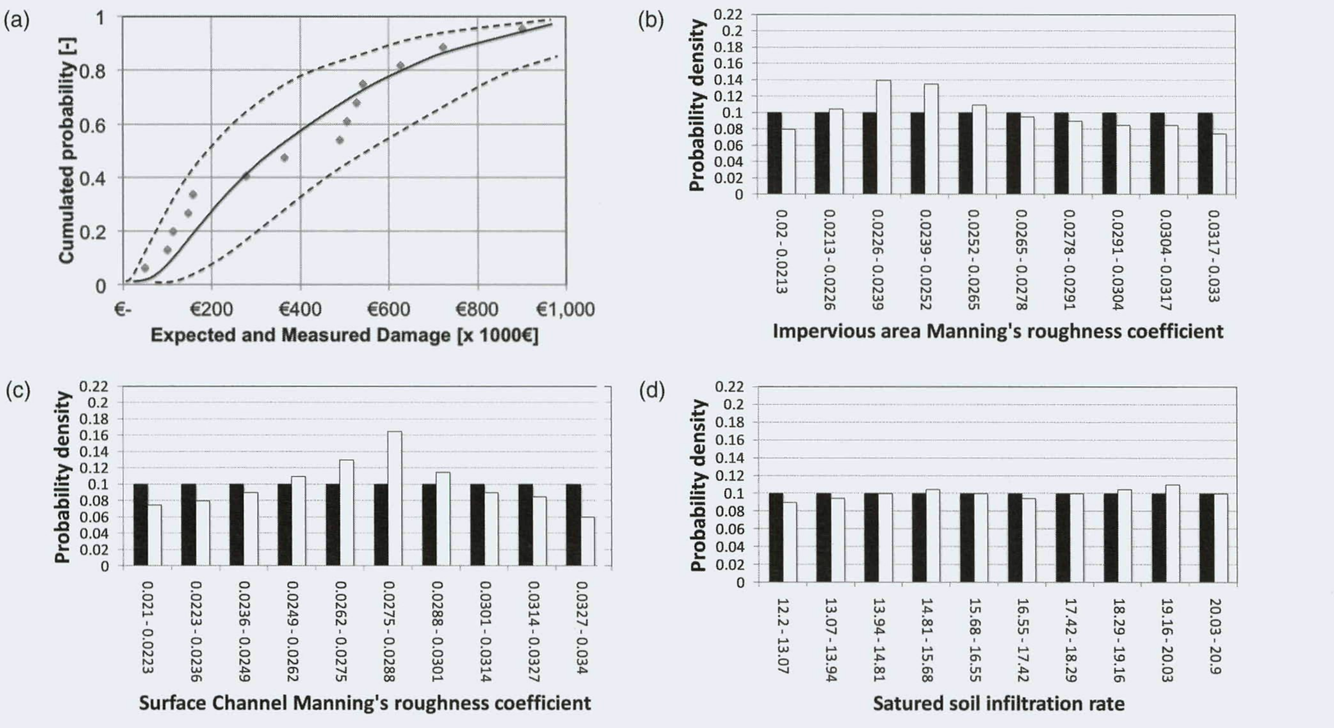

Figure 2 | (a) Uncertainty bands of expected damage, (b–d) prior and posterior distributions for some parameters after the first Bayesian update: dashed lines are the uncertainty bands, black line is the calibrated estimation of flooding damage, dots are measured damage data; black histograms represent prior parameter distributions; white histograms represent posterior parameter distributions.

roughness and surface channel Manning's roughness) and of a non-influential parameter (saturated soil infiltration rate).

The uncertainty band is wide and includes measured data thus allowing for the acceptance of the modelling hypotheses for the analysis of expected damage (Figure 2(a)). The differences between posterior and prior parameter distributions are evident for the two most influential parameters showing the ability of the model to drain information from data used for the analysis (Figures 2(b) and 2(c)). The two parameters have an evident peak thus the Bayesian analysis can be easily used for model calibration as well. Figure 2(d) shows that the posterior distribution of a non-influential parameter is almost unchanged after the analysis of the first data subset thus demonstrating that the model is insensitive to that parameter.

Figure 3 shows the results of the second Bayesian update. The analysis began from the parameter posterior distributions obtained in the analysis of the first data subset. These distributions were used as prior knowledge for the second Bayesian update in order to evaluate the behaviour of Bayesian analysis when new data become available. Figure 3(a) shows that uncertainty band, obtained by ranking the simulated damage values provided by MCSs, is smaller than in the previous step thus showing a reduction in modelling uncertainty due to the availability of new data. The reduction in the average uncertainty band width is about 40%. All available data are still included in the band thus showing that the additional data increased model robustness without affecting its reliability. Posterior distributions of influential parameters are modified during the analysis exalting the peaks and increasing the probability that the parameter values fall around the calibration value (Figure 3(b) and 3(c)). The effect of non-influential parameter (Figure 3(d)) is still low thus confirming the model insensitivity to that parameter.

The final Bayesian update phase (Figure 4(a)) shows a further reduction in the uncertainty band width (−12% in the average) with only 3% of data falling outside of the band. This confirms the applicability of the model considering that the residual probability left out of the 5% and 95% bands is 10% (Beven & Binley 1992). Parameter distributions are further few modified by the introduction of new data in the analysis as well (Figure 4(b) and 4(c)).

The comparison of Figures 3 and 4 demonstrates that distributions are now stabilised. The subjectivity in the choice of the initial parameter distributions has no more effect on the analysis after the second update and this result comforts the decision makers about the reliability of the analysis when the initial information is scarce.

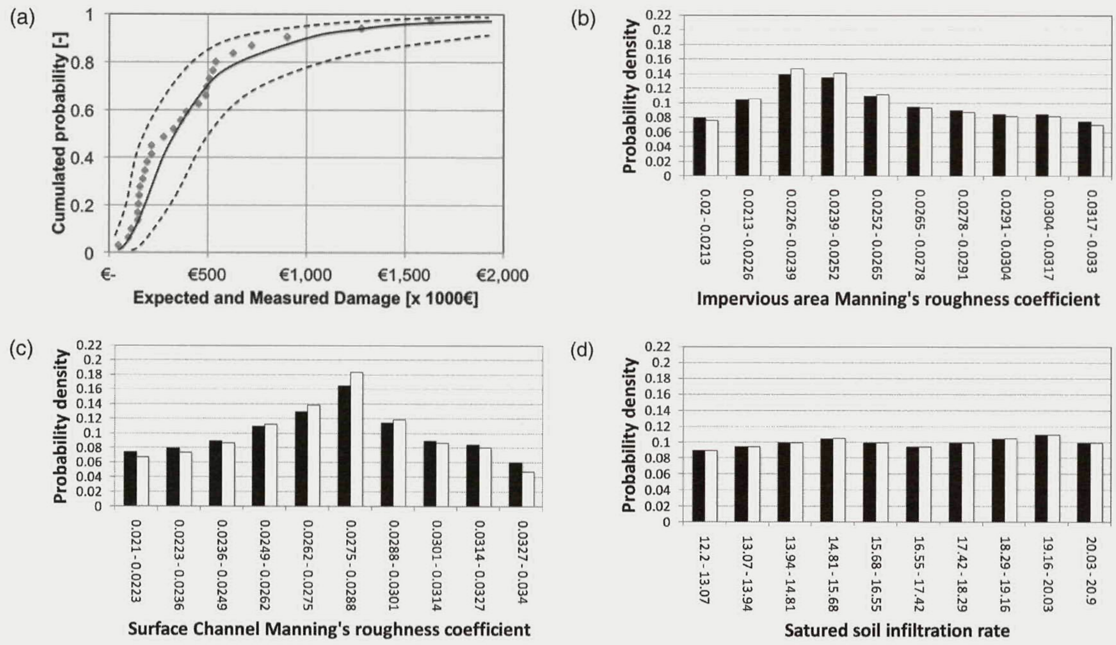

Figure 3 | (a) Uncertainty bands of expected damage, (b–d) prior and posterior distributions for some parameters after the second Bayesian update: dashed lines are the uncertainty bands, black line is the calibrated estimation of flooding damage, dots are measured damage data; black histograms represent prior parameter distributions; white histograms represent posterior parameters distributions.

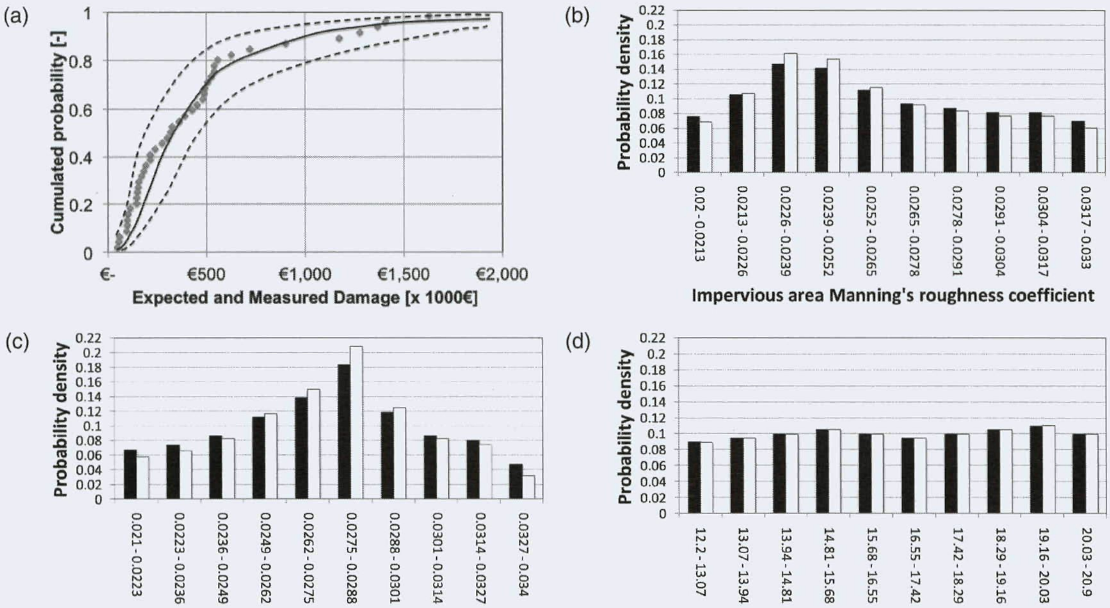

Figure 4 | (a) Uncertainty bands of expected damage, (b–d) prior and posterior distributions for some parameters after the third Bayesian update: dashed lines are the uncertainty bands, black line is the calibrated estimation of flooding damage, dots are measured damage data; black histograms represent prior parameter distributions; white histograms represent posterior parameters distributions.

CONCLUSIONS

The present paper shows the application of Bayesian uncertainty analysis to flooding damage evaluation. The approach was applied in three subsequent update phases in order to evaluate the impact of new available data in uncertainty estimation. The analysis demonstrated that Bayesian approach is effective in the definition of modelling uncertainty and in the guide of calibration process. This method is also suited for the applications, like the analysis of urban flooding, in which data are scarce and become progressively available when new flooding events occur. Damage estimation uncertainty is progressively reduced when new data are used in the analysis and model parameters calibration can be progressively more precise once new data updates are provided. The Bayesian approach is able to highlight non-influential parameters that can be neglected during model calibration process.

The subjectivity given by the selection of prior knowledge has an impact on the process limited to the first update phase; once the first posterior distribution is obtained, the process is no longer affected by the definition of the prior parameter distribution. This shows the effectiveness of Bayesian paradigm in the analysis of flooding damage: the decision makers can start the analysis with a small database about the system and the approach reflects the reliability of available data by providing large uncertainty bands and almost uniform parameter distributions. When new data become available, the analysis can be updated and, if data quality is good, the uncertainty is reduced and parameter distributions shrink around the calibration values. The marginal effect of new data is progressively reduced and uncertainty band width should tend to an asymptotic value related to the unavoidable uncertainty due to measurement error and the model simplified hypotheses.

The present paper provides an interesting method to allow the application of numerical models for flooding analysis in cases where small amounts of data are available. In such cases, the proposed approach allows the estimation of the uncertainty connected with flooding analysis, guides the network manager in the collection of data and provides information of the reliability of data that is progressively added to the analysis. The manager has not to wait the end of monitoring campaign to obtain some initial results and he can evaluate the advantages provided by data collection campaigns.

The same analysis can be used in the decision phase because modifications to the network or to the catchment can be evaluated both in terms of expected flooding damage reduction and in terms of uncertainty so that the manager has the possibility to prefer more robust solutions (uncertainty about the possible damage reduction is lower) than more performing ones.

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