Stochastic Urban Pluvial Flood Mapping Based Upon a Spatial−Temporal Stochastic Rainfall Generator

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ABSTRACT

Traditionally, urban pluvial flood likelihood is estimated by associating the same return period of the original rainfall; however, when the spatial variability of the rainfall plays an important role in the catchment response, this may not be true. In this study, a methodology to assess urban flood hazard maps stochastically is presented. First, a stochastic rainfall generator for urban-scale applications is employed to generate spatial−temporal varying design storms. Each design storm was applied to a 1D/2D drainage model to generate a flood map. Based on all the hydraulic results obtained (water depth and flood extent), flood hazard maps were elaborated. The flood simulation results obtained using the stochastically generated rainfall events, for the Cranbrook catchment, London, UK, showed that rainfall variability plays an important role in the generation of flood maps. The methodology presented in this paper is being further developed to generate flood risk maps, taking into account the rainfall uncertainty impact on flooding, including the analysis of the flood consequences.

KEYWORDS
Urban pluvial flooding, flood hazard mapping, stochastic, radar rainfall, spatial−temporal

INTRODUCTION
Urban pluvial flooding frequency is expected to increase not only due to urbanisation but also to expected climate changes (Ugarelli et al., 2011). This type of flooding can happen virtually anywhere and has the potential to cause significant damage and disruption in highly urbanised areas, where the density of properties, critical infrastructure and population is usually high. The European Directive 2007/60/CE (European Parliament & Council, 2007) on the assessment and management of flood risks, requires that Member States assess the risk of flooding; to fulfil this requirement, flood risk maps are used to classify the likelihood of flooding and quantify its consequences. Due to the density and complexity of the urban built environment, it is essential to accurately identify flood-vulnerable areas.

Traditionally, uniform design storms have been used in the design, planning and evaluation of drainage systems. While the use of design storms is handy for many hydrological and hydraulic applications, the traditional uniform design storm concept neglects the impact of the spatial variability of rainfall fields; this may lead to substantial overestimation of risk which can have large financial implications.

In this paper a methodology is presented to stochastically assess urban pluvial flood hazard, based upon a stochastic spatial-temporal rainfall generator (McRobie et al., 2013). In the proposed methodology, spatially and temporally varying rainfall events are firstly sampled from the generator and then fed into urban pluvial flood models. The resulting hydraulic outputs are statistically analysed in order to estimate the likelihood of a given location being flooded (i.e. probabilistic flood hazard). Figure 1 illustrates the general approach used for generating the stochastic urban pluvial flood hazard maps. The proposed approach is tested in a small urban catchment (~9 km^2) located in North East London with a history of pluvial flooding. In the following sections the different components of the methodology as well as the pilot location used to demonstrate it are described.
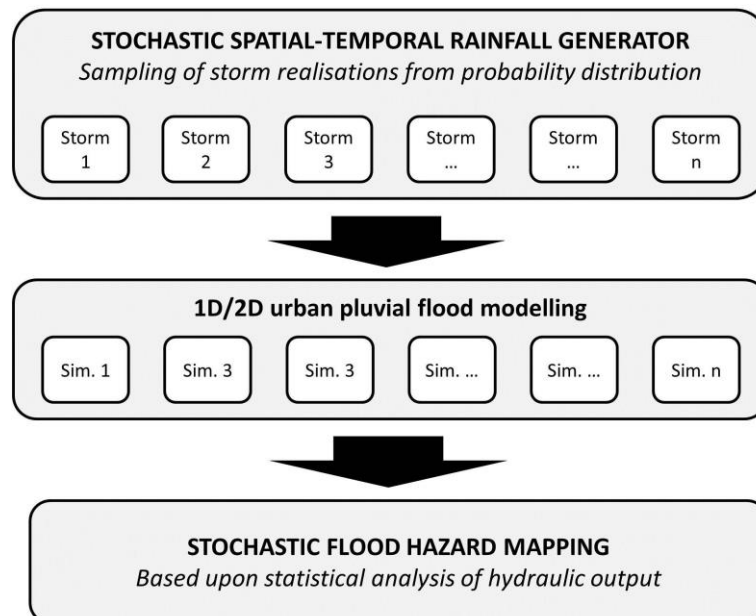

Figure 1. General approach for generation of stochastic urban pluvial flood hazard maps based upon a stochastic spatial-temporal rainfall generator

PILOT LOCATION: THE CRANBROOK CATCHMENT

Catchment description: The Cranbrook catchment is located within the London Borough of Redbridge (north-east part of Greater London - Figure 2). It has a drainage area of approximately 9 km^2 and is predominantly urban, with a combination of residential and commercial areas, in addition to two off-line lakes, a couple of parks and playing fields. It has a population of approximately 41,000 inhabitants (population density ~47.7 persons per hectare) and the main industries of employment are real state renting and business activities, wholesale and retail trade, and health and social work.

The main water course (i.e. the Cran Brook) is about 5.75 km long, of which 5.69 km are culverted and have become part of the storm water drainage system, which is mainly

separate. The storm water drainage system of this catchment discharges into the Roding River and, in turn, the Roding River discharges into the river Thames. This area has experienced several pluvial, fluvial and coincidental flooding in the past.

Hydraulic model: A 1D/2D dual-drainage, physically-based model of the Cranbrook catchment was setup in InfoWorks CS 14.0. In this model the urban surface was modelled in 2-dimensions (2D), using an irregular triangular mesh. The model of the surface was coupled with a 1-dimensional (1D) model of the sewer system which comprises 1,763 nodes and 1,816 pipes. Rainfall is applied to the model through subcatchments, in which runoff is estimated using the NewUK model. Subcatchments are linked to the nodes of the 1D sewer model; as such, flood water only reaches the surface once sewers surcharge. The model was verified in 2011 using data from a local monitoring system operated by the authors of the paper since 2010 (Simões, 2012; Wang et al., 2013)(see Figure 2).
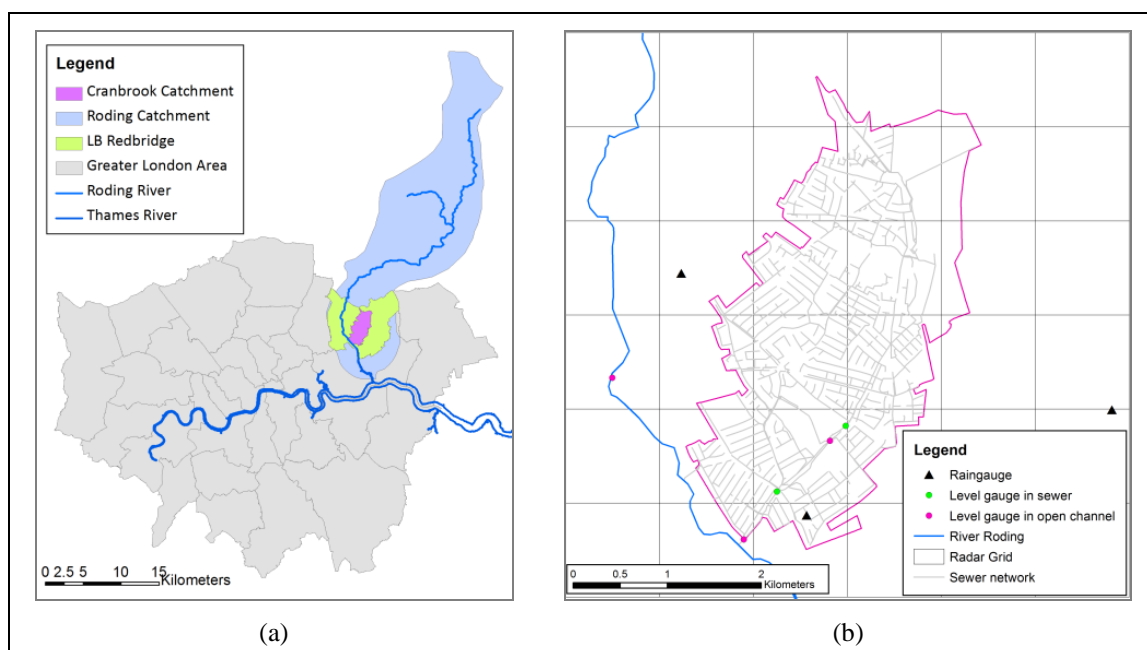

Figure 2. Cranbrook catchment (a) general location; (b) sensor location, sewer network and radar grid over the catchment.

SPATIAL-TEMPORAL STOCHASTIC RAINFALL GENERATOR

A stochastic rainfall generator for urban-scale applications was employed in this work to generate spatial-temporal varying design storms. This generator was developed by McRobie et al. (2013). In this generator, storms are modelled as clusters of Gaussian rainfall cells, extending the earlier method proposed by Willems (2001) to radar rainfall data. The parameters describing the cells and their motion are sampled from probability distributions derived from parameter estimates gained from 45 historical storm events, which have been identified as significant events causing flooding over Greater London area for the period 2000-2011. These parameter sets, the fitted distribution models and distribution parameters are summarised in Table 1.

This generator was used to sample over 450 design storm realisations, and according to the ranking of rainfall maxima in 60-min duration, the top 45 realisations were selected and used as input for hydraulic modelling. The distributions of the selected storm durations and the

rainfall maxima (in mm, at one radar pixel) in 15-, 30- and 60-min duration are summarised in Figure 3.

Table 1. Summary of parameter set and the fitted distributions thereof

| Parameter Set	Fitted Distribution	Distribution Parameters
Storm Duration (d)	Gamma	a (-) = 2.44, b (hrs) = 17.92
Number of Cells Per Square Kilometre (λ)	Normal	μ (km^{-2}) = 0.0099, σ (km^{-2}) = 0.0032
Velocity Magnitude (v)	Log Normal	μ (km/hr) = 78.30, σ (km/hr) = 23.64
Velocity Direction (θ)	Log Normal	μ (rads) = 0.51, σ (rads) = 1.16
Cell Spread in Direction of Motion (s_1)	Log Normal	μ = 0.700, σ = 1.260
Cell Spread in Direction Perpendicular to Motion (s_2)	Log Normal	μ = 0.704, σ = 1.201
Maximum Intensity in Cell (r_{max})	Generalised Pareto	k = 0.586, σ = 1.040, θ = 5.0 mm
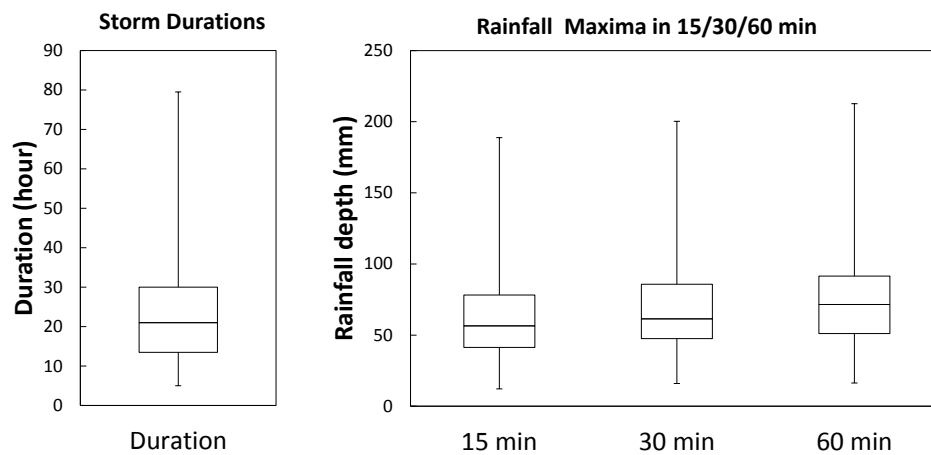
Figure 3. Boxplots of selected storms' features: (left) storm duration in hour, and (right) rainfall maxima (at one radar pixel) in 15-, 30- and 60-min time duration.

STOCHASTIC FLOOD HAZARD MAPPING

The conventional methodology to generate flood maps takes into account a specific rainfall event (in many cases a design hyetograph), with a defined return period. The hydraulic simulation results are thus based on a single hydraulic modelling simulation and may not illustrate the real flood likelihood. The rationale of the novel methodology presented in this paper aims at taking into account rainfall variability as these can significantly affect hydraulic simulation results, as discussed in other papers (Leitão et al., 2009; Gires et al., 2012; Schellart et al., 2012), in order to generate flood maps that incorporate such variability and represent flood uncertainty.

The proposed methodology uses the spatial-temporal stochastic rainfall to generate a stochastic flood map, i.e. a flood map that incorporates the stochastic nature of the rainfall. To demonstrate the proposed methodology, forty five simulations were carried out, each of them using the rainfall realisations generated in the previous step. Apart from the different rainfall input, no other changes were carried out in the hydraulic model. The results were filtered out based on a water depth threshold; in this case, only cells with water depth higher than 0.05 m were considered as flooded locations.

Taking into consideration the results of the 45 hydraulic simulations, the least and most extreme rainfall events correspond to storms (rainfall realisations) number 7 and 45, respectively. Table 2 presents flooded area values.

Table 2. Summary of the hydraulic simulations

Flood extent (m^2)		
Minimum	Maximum	Average
622	872,330	235,455

Figure 4a shows the flood extent obtained from the most extreme storm event (event number 45). In Figure 4b the three images represent the flood extent results obtained using storms 45 (most extreme event), 3 (intermediate event) and 7 (least extreme event). As can be seen in the image at the bottom of Figure 4b, rainfall event 7 only causes flooding in a very small area. In contrast, the maximum flood extent is clearly visible and affecting a large area of the catchment for the two other storm events (especially for storm number 45). Storm event 45 has the maximum flood extent, however in figure 4b, event 3 shows larger flood extent in this specific area, which shows the importance of taking into account the spatial variability of the rainfall event.
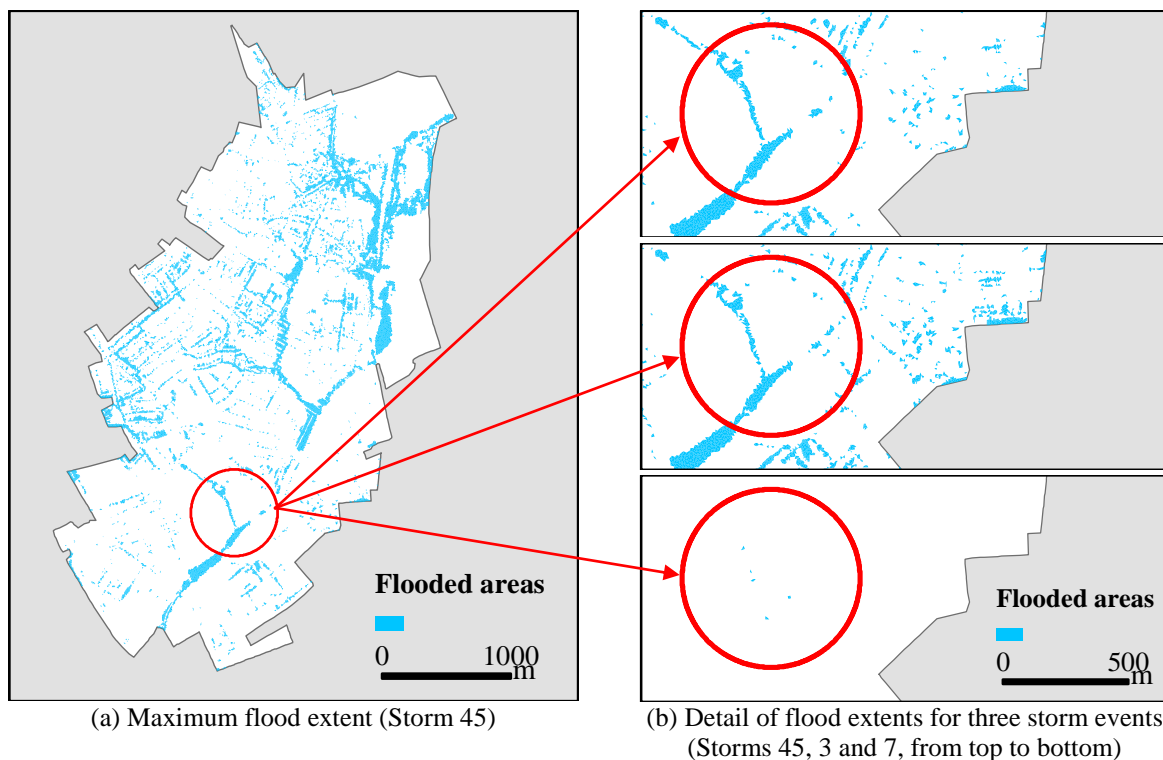

(a) Maximum flood extent (Storm 45) (b) Detail of flood extents for three storm events (Storms 45, 3 and 7, from top to bottom)

Figure 4. Simulated flood extent for three storm event realisations of different magnitude.

The ultimate goal of the stochastic analysis presented in this paper is to generate stochastic flood maps, i.e. where in the catchment flood is more likely to occur. This is achieved by calculating the number of times a given area is flooded (an area is the polygon of the surface mesh used in the 2D overland flow modelling). The results of this analysis are presented in Figure 5. This figure shows that some locations get flooded with every rainfall event considered in this study. In contrast, other locations get flooded only a few times, and the majority of the catchment seems not to be affected by flooding.
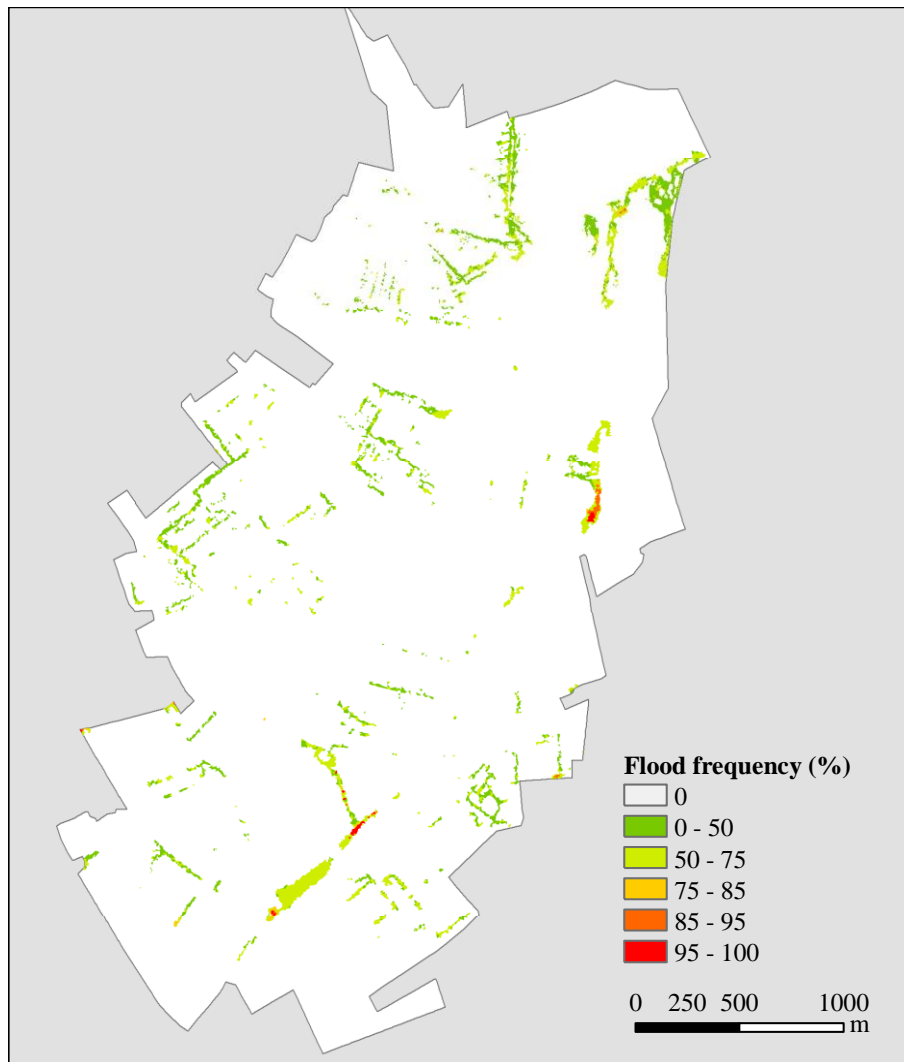
Figure 5. Modelled flood probability based on spatial-temporal stochastic rainfall.

The above results highlight the importance of taking into consideration rainfall variability and uncertainty. This can support decision makers in implementing actions in areas where flooding is more likely to occur, thus reducing flood risk in those areas.

CONCLUSIONS AND OUTLOOK

Traditionally, the return period of a flood event is defined based on return period of the rainfall time series. This may be insufficient due to the rainfall variability that may affect the flood, i.e. different rainfall events with the same return period can generate flood with different magnitude (water depth and flood extent). In this paper, a methodology to assess urban flood hazard maps stochastically was presented. Firstly a stochastic rainfall generator for urban-scale applications was employed to generate spatial-temporal varying design storms. Each design storm was applied to a 1D/2D drainage hydraulic model to generate flood maps. Based upon all the resulting hydraulic outputs (i.e. water depth and flood extent), flood hazard maps were elaborated.

The use of a stochastic spatial-temporal rainfall generator enables the generation of relatively realistic storms with spatial and temporal variability. This leads to a very different thought from the current definition of design storms, of which the spatial distribution is assumed to be uniform. Furthermore, this new concept creates an open question about the use of return

6

period to characterise spatial and temporal variable storms; this is worthy to be further investigated.

The flood simulation results obtained using the stochastically generate rainfall events, for the Cranbrook catchment, showed that rainfall variability may play an important role in the generation of flood maps. The results presented herein aim at demonstrating the applicability of the proposed methodology. The case demonstrated in this paper used merely 45 stochastic generated rainfall events. This number of realisations can be considered limited to incorporate the possible variability of rainfall (spatial and temporal variations); thus the authors suggest that in future studies a larger number of rainfall realisations and respective hydraulic simulations should be conducted. Besides the flood depth and extent, other parameters may be included, such as velocity and velocity/water depth ratio.

The methodology presented in this paper is being further developed to generate flood risk maps, taking into account the rainfall uncertainty impact on flooding, including the concept of flood risk. The results presented herein can be used as the likelihood (or probability) part in the risk function, $R = f(P, C)$.

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