

1 Influence of urban forms on surface flow in urban pluvial flooding

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29 This paper presents a systematic analysis of the influence of nine urban characteristics (distance be-
30 tween buildings, mean building size, building coverage, etc.) on surface flow in case of pluvial
31 flooding. Time dependent stored volumes, outflow discharges and mean water depths were com-
32 puted for a set of 2,000 synthetic urban forms, considering various terrain slopes and return periods
33 of the rainfall. An efficient porosity-based surface flow model was used to compute the 2D flow
34 variables. Statistical analysis of the relationship between the flow and urban variables highlights
35 that the flooding severity is mostly influenced by the building coverage.

36 *Keywords: urban pluvial flood, porosity shallow-water model, procedural modelling.*

37 1 INTRODUCTION

38 Worldwide, urban flooding induces a broad range of damage to people, infrastructure and economy
39 (e.g. Huang et al., 2017, Yin et al., 2016, Kreibich et al. 2019). Urban flood risk is growing as a re-
40 sult of rapid urbanization and increasingly frequent hydroclimatic extremes (Zhou et al. 2012, Chen
41 et al. 2015, Muis et al. 2015, Yin et al. 2015, Miller and Hutchins 2017). A major cause of flooding
42 in inland urban areas is pluvial floods, induced by heavy rainfall events (Gaines 2016). Existing re-
43 search on urban pluvial flooding has covered a broad range of aspects, including spatio-temporal
44 precipitation data, rainfall-runoff modelling, risk management and impact analysis of climate and
45 land-use change.

46 1.1 Existing data and models

47 Hydrological modelling of urban catchments remains particularly challenging due to (i) limitations
48 in data availability, (ii) specific flow processes such as the interactions between surface flow and
49 urban drainage systems, (iii) as well as the spatial heterogeneity of urban features influencing runoff
50 (Leandro et al. 2009, Salvadore et al. 2015).

51 In early studies, the urban surface water runoff originating from point sources, such as manholes,
52 has been simulated with 2D surface flow routing models, either based on the full 2D shallow-water
53 equations (Mignot et al. 2006, Martins et al. 2017) or on simplified versions such as inertial formu-
54 lation (e.g. Fewtrell et al.,2011).

55 Other research applied sequentially a 1D model for the urban drainage system and a 2D model for
56 surface flow routing. The outcome of the urban drainage model consists in hydrographs of sur-
57 charged flow (i.e. excess flow compared to the design discharge of each pipe section), used as an
58 input for the 2D surface flow routing model. Based on this approach and a 2D diffusive surface
59 flow model, Hsu et al. (2000) simulated inundation in urban areas caused by the surcharge of storm
60 sewers and considering the influence of pumping stations. Nonetheless, even in this approach, two-
61 way interactions between the surface flow and the urban drainage system are not reproduced explic-
62 itly.

63 In contrast, *dual-drainage* modelling consists in coupling a 1D flow routing model for the urban
64 drainage system and a 2D surface flow routing model (Schmitt et al. 2004, Djordjević et al. 2005,
65 Chen et al. 2007, Seyoum et al. 2012, Löwe et al. 2017). The bidirectional interactions between the
66 two models are ensured through sink and source terms in the respective model equations. These
67 terms are evaluated from weir or orifice formulae (Bazin et al. 2014). In so-called *hydro-inundation*
68 *models*, precipitation is incorporated as a source term in the 2D surface flow routing model and this
69 model contains an explicit representation of hydrological processes such as infiltration (Cea et al.
70 2010, Yu and Coulthard 2015, Leandro et al. 2016, Löwe et al. 2017) and evaporation (Yu and
71 Coulthard 2015, Yin et al. 2016, 2019) , to replace the total rainfall by the effective rainfall. While
72 in conventional approaches catchment modelling and floodplain modelling are two successive
73 steps, in hydro-inundation models they are merged into a single computation. In several studies,
74 dual-drainage and hydro-inundation features were combined (Hsu et al. 2000, Schmitt et al. 2004,
75 Leandro et al. 2016). In contrast, others opted for a simplified description of the urban drainage sys-

76 tem, such as assuming that water is drained away at the design capacity, without explicit representa-
77 tion of drains and manholes (Yu and Coulthard 2015, Yin et al. 2016, 2019), or even neglected the
78 urban drainage system (Huang et al. 2017). In existing dual-drainage and hydro-inundation models
79 so far, the surface flow was represented using non-inertia 2D flow models.

80 The broad range of developed models has proved valuable to support urban flood risk management
81 as well as for the planning and management of urban drainage systems (Fletcher et al. 2013). They
82 have been used in various settings, including for evaluating the impact of flooding on traffic interrup-
83 tion (Yu and Coulthard 2015, Yin et al. 2016, 2019), for urban flood forecasting (Chen et al. 2015),
84 for assessing pluvial flood risk at the local level (Elboshy et al. 2019), among other applications.

85 *1.2 Influence of urban planning on urban pluvial flooding*

86 Many recent studies have investigated the sustainable management of urban storm water based on
87 Low Impact Development (LID) techniques (i.e. seeking to mimic a site's pre-development hydrology),
88 such as tanks, swale, green roof or permeable pavement (Qin et al. 2013, Ahiablame and
89 Shakya 2016, Chen et al. 2017). Others analysed the impacts of urbanization on urban pluvial
90 flooding. For instance, based on a hydro-inundation model, Huang et al. (2017) and Miller and
91 Hutchins (2017) highlighted that land-use and land cover changes substantially contribute to in-
92 crease pluvial flooding in urban areas, especially for extreme rainfall events.

93 However, a more limited attention has been paid so far to the specific influence of urban planning
94 policies on urban pluvial flooding. In this regard, only a study carried out by Löwe et al. (2017)
95 stands out. For an urban catchment of 300 ha in Australia, they coupled a 1D-2D hydrodynamic
96 model with an urban development model. They tested nine different urban development scenarios,
97 characterized by contrasting levels of demand for housing, type and location of buildings (uncon-
98 trolled urban sprawl involving detached single-unit houses *vs.* more compact urban forms with
99 multi-storey buildings and apartment blocks) as well as flood adaptation options (buyback of prop-

100 erties, rainwater harvesting, increased stormwater pipe capacity). Their results suggest that, com-
101 pared to the increase of urban drainage capacity, urban planning policies are more efficient to re-
102 duce flood risk under various climate change scenarios.

103 Nonetheless, even Löwe et al. (2017) paid only limited attention to the role paid by the urban form
104 on the severity of urban pluvial flooding, whereas geometry and arrangement of buildings alter the
105 surface flow preferential directions as they represent obstacles to the flow (Leandro et al. 2016).
106 Additionally, existing research focused on individual real-world case studies, and not on more ge-
107 neric configurations; and previous analyses remained generally at the level of the land-use category
108 (e.g. residential, industrial vs. green space), not at the building level.

109 Therefore, in this paper, we aim to understand whether the geometric characteristics of the arrange-
110 ment of buildings (also called *urban pattern*) influence surface flow during urban pluvial flooding.
111 More specifically, using regression and correlation analyses, we have been searching for possible
112 relationships between indicators of the severity of urban flooding (stored volume, inundation depth,
113 outflow discharge) and geometric parameters characterizing the urban patterns (typical street width,
114 length, curvature and orientation, building size and distances between buildings).

115 To do so, we performed a systematic analysis by considering 2,000 synthetic, but realistic, urban
116 forms, obtained from a procedural urban generation model. For each of them, we computed the sur-
117 face flow variables corresponding to three different design rainfalls (15-, 50- and 100-year return
118 periods). The terrain slope was also varied, resulting in a total of 12,000 distinct simulations. This
119 analysis is an extension of the procedure recently developed by (Bruwier et al. 2018) for the case of
120 river flooding.

121 To perform the high number of necessary model runs, we used an efficient hydro-inundation model
122 developed in-house. It is based on a validated integral porosity shallow-water model solving the
123 fully dynamic shallow-water equations for surface flow (Bruwier et al. 2017a). A simplified ap-

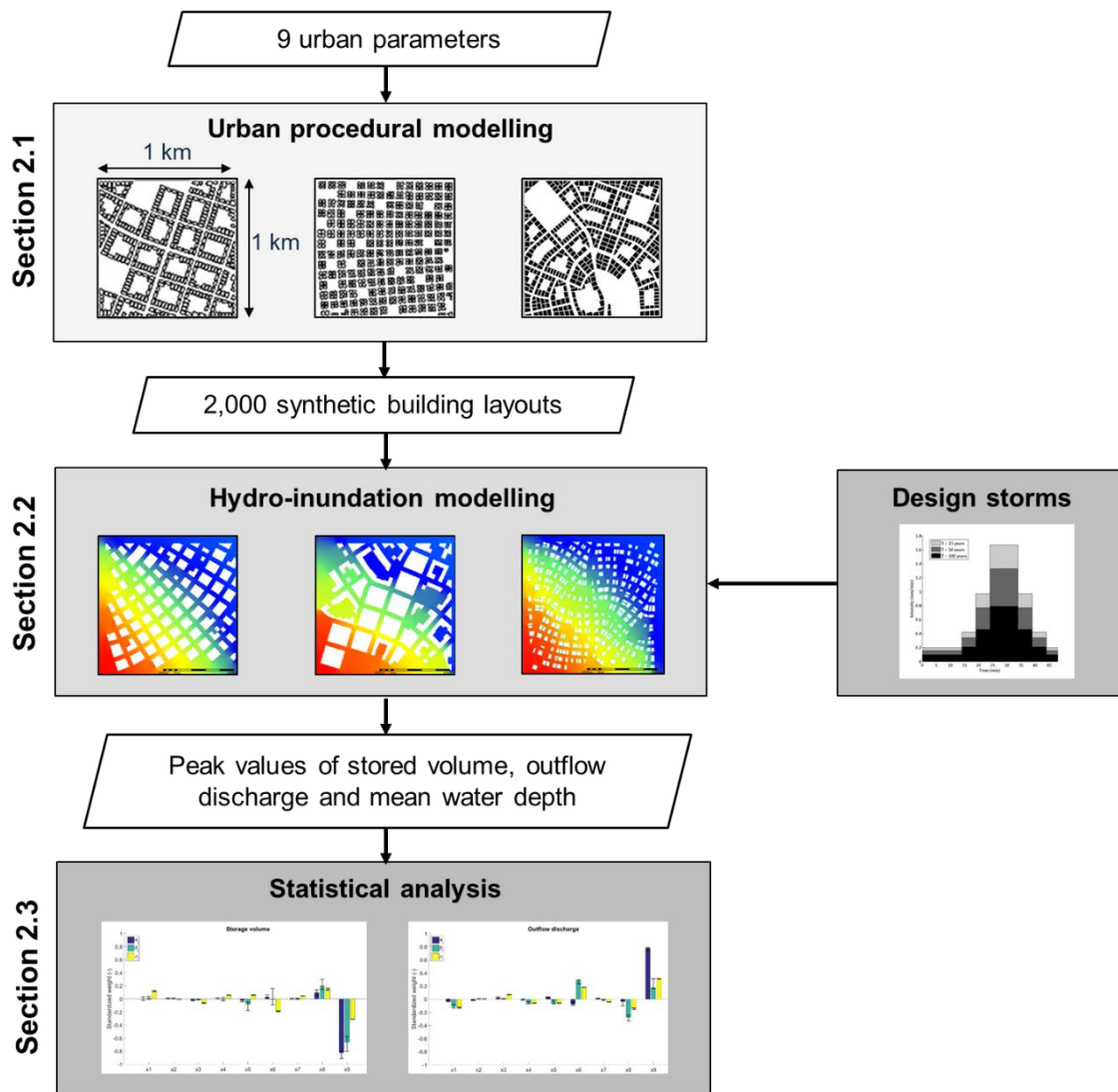
124 proach is used to represent the urban drainage system, which is deemed justified here since the fo-
125 cus is set on comparing the influence on surface flow of the geometric parameters characterizing the
126 urban patterns.

127 The methodology, detailed in Section 2, includes the generation of synthetic urban forms with a
128 procedural model (Section 2.1), a brief presentation of the hydro-inundation model (Section 2.2)
129 and the statistical approach used to determine the impact of urban parameters on pluvial flow (Sec-
130 tion 2.3). Computed flow variables and their relationships with the urban characteristics are pre-
131 sented and discussed in Section 3. Conclusions are drawn in Section 4.

132 2 METHODOLOGY

133 The methodology for evaluating the influence of the urban forms on urban pluvial flooding consists
134 of a chain of two modelling steps and one statistical analysis step, as sketched in Figure 1. Each
135 step is detailed in the following sections:

- 136 • Section 2.1 presents the generation of 2,000 synthetic urban forms by means of proce-
137 dural modelling;
- 138 • Section 2.2 describes the computation of surface flow using a porosity-based shallow-
139 water model and design storms of various return periods;
- 140 • Section 2.3 details the statistical analysis developed to assess the influence of each urban
141 parameter on the peak values of stored volume, outflow discharge and mean water depth.



142
 143 Figure 1: Methodology involving procedural modelling, hydro-inundation modelling
 144 and statistical analysis.

145 **2.1 Procedural modelling**

146 Synthetic urban forms were generated using a deterministic *procedural modelling* system presented
 147 by Mustafa et al. (2018). It consists of a set of rules which enable defining the street network and
 148 the arrangement of parcels and buildings based on a limited number of input parameters. The out-
 149 puts of this urban procedural modelling are collections of locations and footprint geometries of
 150 buildings over a predefined area. In this study, we considered a square area of 1 km by 1 km and we
 151 generated 2,000 distinct urban forms by randomly selecting the values of the input parameters.

152 The input parameters are listed in Table 1. They are identical to those used by Bruwier et al. (2018).

153 The procedural model operates in three steps:

- 154 • The network of streets is made of two perpendicular “major” streets and a number of
155 “minor” streets. The skeleton of the network of streets is controlled by parameters x_1 to
156 x_3 . Parameter x_1 defines the typical distance in-between street intersections. The street
157 orientation is controlled by parameter $x_2 = | \sin [2 (\alpha - \pi / 4)] |$, with α the angle be-
158 tween the west-east direction and the alignment of one of the two main streets. The cur-
159 vature of the streets is given by x_3 (reciprocal of the typical radius of curvature).
- 160 • Parameters x_4 to x_6 influence the number and location of the individual parcels.
- 161 • The size and location of the buildings within each parcel are governed by the setbacks x_7
162 and x_8 , which represent distances between buildings and the borders of the parcels. The
163 building coverage x_9 is the fraction of the total area occupied by buildings. It controls the
164 number of parcels kept without building (i.e. open space).

165 As shown in Table 1, each input parameter was restricted to a range of variation defined to ensure a
166 sufficient degree of realism of the generated urban forms. These ranges of variation were derived
167 from a sample of real-world cadastral data from Belgium. Nonetheless, the procedural model can
168 also represent a broad range of other urban forms, especially for European cities, as shown by Mus-
169 tafa et al. (2018).

170 A complete description the flow process of the procedural model is given by Bruwier et al. (2018).

171 Examples of generated urban forms are shown in Figure 8 hereafter, as well as in Bruwier et al.
172 (2017a, 2018) and Mustafa et al. (2018).

	Urban variable	Minimum	Maximum
x_1	Average street length	40 m	400 m
x_2	Street orientation	0	1
x_3	Street curvature	0 km ⁻¹	10 km ⁻¹
x_4	Major street width	18 m	38 m
x_5	Minor street width	10 m	21 m
x_6	Mean parcel area	350 m ²	1,100 m ²
x_7	Building rear setback	1 m	5 m
x_8	Building side setback	1 m	5 m
x_9	Building coverage	0%	43%

Table 1: Input parameters characterising the synthetic urban forms,
and ranges of variation.

To perform flow computations, the building footprints generated by procedural modelling are placed on an idealized terrain of uniform slope along the direction south-west (highest level) to north-east (lowest level) (Figure 2). Two distinct slopes were tested: 1.4% and 2.8%. Idealizing the topography as a plane is a strong assumption; but it is motivated by our intention to focus here our systematic analysis on the influence of the urban forms. Therefore, we did not want to include additional independent variables characterizing a more complex topography (e.g. location, extent, depth of sinks ...).

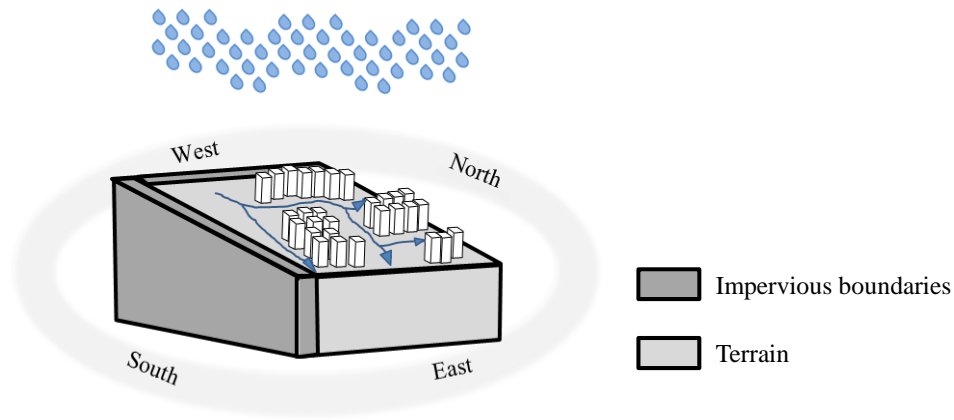


Figure 2: Schematic representation of the considered 1 km by 1 km urban district on a terrain of uniform slope, with building footprints.

2.2 *Hydro-inundation model*

For each of the 2,000 synthetic urban forms introduced in Section 2.1, surface flows occurring during urban pluvial flooding were computed under identical flow boundary conditions and hydrological forcing (design storms).

To perform the flow computation, we used an existing porosity-based shallow-water model. Such porosity-based models enable using relatively coarse computational cells while preserving to some extent the detailed topographic information at a subgrid-scale by means of storage and conveyance porosity parameters (Sanders et al. 2008). This approach enables speed-up factors of the order of 10^2 to 10^3 compared to standard shallow-water models, while keeping a similar level of accuracy (Guinot et al. 2017). This made the systematic analysis of 2,000 urban forms tractable.

We applied here the same porosity-based model as used by Bruwier et al. (2018) for assessing the influence of the urban forms in the case of river flooding. The model was introduced and extensively validated by Bruwier et al. (2017a). It was also repeatedly applied for modelling urban flooding (Arrault et al. 2016, Bruwier et al. 2017b, 2018). An additional piece of validation against experimental observations is provided in Supplementary material A for flow conditions corresponding specifically to pluvial flooding.

205 The flow computations were performed using a Cartesian grid with a spacing $\Delta x = 10$ m, a Manning
206 roughness coefficient $n = 0.01 \text{ sm}^{-1/3}$, a drag coefficient $c_D = 2$ and a minimum threshold porosity
207 $\phi_{\min} = 0.1$. The influence of these parameters, particularly the grid size, was tested by Bruwier et al.
208 (2017a) for geometric configurations (urban forms) identical to those considered here.

209 As sketched in Figure 2, impervious upstream boundaries were prescribed along the south and west
210 sides of the urban district, while a rating curve was prescribed as a downstream boundary condition
211 along the north and east sides. This rating curve is a lumped representation of the flow conditions
212 further downstream of the urban area under study. It relates the local runoff unit discharge to the
213 power $3/2$ of the runoff depth (Bruwier et al. 2018). The buildings are represented as impervious
214 blocks.

215 The specific objective of the present study is not to represent a given real-world flooding event, but
216 instead to conduct a comparative analysis of the influence of urban characteristics on surface flow
217 during urban pluvial flooding. Therefore, the selection of the rainfall input is to a great extent arbi-
218 trary, provided that it remains representative of real situations. We opted for three distinct design
219 storms corresponding to return periods of 15, 50 and 100 years in a Belgian municipality
220 (Hosseinzadehtalaei et al. 2018). This range of return periods is consistent with that used in other
221 similar researches (Yin et al. 2016, Huang et al. 2017). More details on the design storms are given
222 in Supplementary material B.

223 The model accounts for direct rainfall input but it does not represent the urban drainage explicitly.
224 While in some studies the urban drainage system was assumed overwhelmed and therefore simply
225 neglected (Mignot et al. 2006, Fewtrell et al. 2011), we opted here for a lumped representation of
226 the urban drainage (e.g. Yu and Coulthard 2015) by subtracting a portion of the rainfall input (e.g.
227 Skougaard Kaspersen et al. 2017). Consistently with JBA Consulting (2016), we subtracted from
228 the considered design storm the design storm corresponding to a plausible return period taken into
229 account for the sizing of urban drainage systems. This return period was assumed equal to two

230 years. This simplified approach, assuming that the drainage system drains at its design capacity,
231 makes the model more suitable for events strongly dominated by direct surface runoff.

232 In principle, the spatially distributed effect of drains could be incorporated in the hydro-inundation
233 model; but it was deemed inconsistent with the primary objective of the study, which focuses solely
234 on the influence of the geometry and arrangement of the buildings. Accounting for spatially distrib-
235 uted drains would have required additional arbitrary assumptions (on their location, pipe sizing, net-
236 work topology ...) which could affect our conclusions.

237 In previous studies of urban pluvial flooding, infiltration was either neglected (Brown et al. 2007,
238 Chen et al. 2007, Sampson et al. 2013), replaced by an initial abstraction (Chang et al. 2015, Russo
239 et al. 2015) or computed explicitly by means of dedicated equations such as Green–Ampt (Yu and
240 Coulthard 2015, Leandro et al. 2016, Yin et al. 2016), Horton (Fernández-Pato et al. 2016, Löwe et
241 al. 2017), or a simplification of the former equations (Skougaard Kaspersen et al. 2017). Here, to
242 avoid extra arbitrary assumptions and keep the focus on the primary aim of this exploratory study,
243 all spaces not occupied by buildings were assumed impervious. The cumulative effects of the urban
244 form and green (infiltration) spaces should be analysed separately. Note that, although disregarding
245 the infiltration in green areas is a strong assumption, adding infiltration processes in the present sys-
246 tematic analysis of a broad range of urban forms would dramatically increase the number of inde-
247 pendent variables (spatial distribution, extent and infiltration capacity of green areas), which in turn
248 would make the conclusions less focused on the “effects of urban forms”.

249 Evapotranspiration could safely be neglected due to the urban nature of the catchment and the rela-
250 tively short time scales of interest here (Yu and Coulthard 2015).

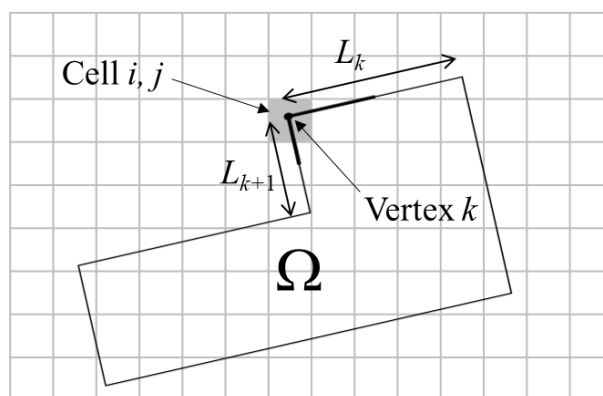
251 Another common challenge in the modelling of urban pluvial flooding relates to the impact of the
252 building roofs on the rainfall–runoff processes, mainly due to a general lack of knowledge on the
253 roofs drainage structure. By introducing a constant user-defined routing velocity for shallow areas
254 (including the roofs of the buildings), Sampson et al. (2013) conducted stable simulations of direct
255 precipitation onto topography where buildings are present, without requiring prior knowledge or

256 roof drainage structures. Chang et al. (2015) utilised some sub-catchments feature of their model to
 257 represent the buildings rainfall–runoff processes. Similarly, Leandro et al. (2016) set up a concep-
 258 tual model to reproduce drainage of the rainfall falling on the buildings roofs.

259 In this study, we opted for a simple conceptual approach, in which we assume that, at every time
 260 step, the total amount of rainfall falling on the roof of a given building is drained instantaneously
 261 and transferred to the surface flow computation in the cells corresponding to the vertices of the
 262 building footprint contour. The rainfall volume reaching a roof over one time step is distributed be-
 263 tween the building contour vertices according to the sum of the lengths of the building facades con-
 264 nected to each corner (Figure 3):

$$265 \quad d_{i,j}(t) = I(t) \Omega \frac{L_k + L_{k+1}}{2} \left(\sum_{m=1}^M L_m \right)^{-1}, \quad (1)$$

266 with $d_{i,j}$ the contribution to the source term in the flow continuity equation due to vertex k of the
 267 considered building, $I(t)$ the rainfall intensity at time t , Ω the footprint area of the considered build-
 268 ing, L_k and L_{k+1} the lengths of the building facades connected to vertex k and M the total number of
 269 vertices in the contour of the considered building.



271
 272 Figure 3: Sketch of a building footprint represented on the Cartesian computational grid
 273 (cells i, j), with Ω the building footprint area, k a vertex of the building contour and L_k ,

274 L_{k+1} the lengths of the building facades adjacent to vertex k .

2.3 Statistical analysis

Three time-dependent flow variables were examined to characterize the severity of urban pluvial flooding:

- the *volume of water stored* within the urban area (V),
- the *outflow discharge* along the downstream sides (Q_{out}), computed as $Q_{\text{out}} = I(t) A - dV/dt$ where A stands for the total surface of the urban area.
- and the *mean water depth* (h_{mean}), computed as a *spatial-average* of the water depth: V / A_f , where A_f is the part of the total urban area not occupied by buildings: $A_f = A (1 - x_9)$.

For each of these flow variables, a statistical analysis was conducted to highlight possible correlations with the nine urban parameters (x_1, \dots, x_9) used as input for procedural modelling (Section 2.1).

The dependent variables considered in the statistical analysis are defined as the variation in the peak value of V , Q_{out} or h_{mean} compared to a reference configuration without buildings:

$$y_1 = -\left(\left[\max_t V \right]_{\text{test}} - \left[\max_t V \right]_{\text{ref}} \right), \quad (2)$$

$$y_2 = \left[\max_t Q_{\text{out}} \right]_{\text{test}} - \left[\max_t Q_{\text{out}} \right]_{\text{ref}}, \quad (3)$$

$$y_3 = \left[\max_t h_{\text{mean}} \right]_{\text{test}} - \left[\max_t h_{\text{mean}} \right]_{\text{ref}}, \quad (4)$$

where subscripts “test” and “ref” refer respectively to any of the 2,000 tested urban configurations, and to a reference configuration without buildings. Eq. (2) ensures positive values of y_1 since the peak value is maximum in the absence of buildings (section 3.2).

To ensure the robustness of the conclusions, we used three distinct approaches for the correlation and regression analyses:

- first, a multiple linear regression (MLE) was applied to standardized variables:

297
$$\frac{y_j - y_{j,\text{mean}}}{y_{j,\text{std}}} = a_{0,j} + \sum_{i=1}^9 a_{ij} \frac{x_i - x_{i,\text{mean}}}{x_{i,\text{std}}}, \quad (5)$$

298 where a_{ij} ($i = 0$ to 9 , $j = 1$ to 3) are the coefficients of the MLR, while the subscripts “mean” and
 299 “std” denote respectively the mean and the standard deviation of the corresponding variable
 300 over the sample of 2,000 urban configurations;

- 301 • second, a multiple linear regression was applied to the logarithmic transformation of normalized
 302 variables, which is equivalent to:

303
$$\frac{y_j}{y_{j,\text{mean}}} = b_{0,j} \prod_{i=1}^9 \left(\frac{x_i}{x_{i,\text{mean}}} \right)^{b_{ij}}, \quad (6)$$

304 with $b_{0,j}$ a coefficient and b_{ij} the exponents of the normalized explanatory variables x_1 to x_9 ;

- 305 • third, Pearson correlation coefficients ρ_{ij} were computed.

306 3 RESULTS

307 In the following, we present the results of the flow computation (Section 3.1) and the outcomes of
 308 the statistical analysis (Section 3.2). We also discuss which are the most influential urban parame-
 309 ters (Section 3.3).

310 3.1 Flow variables

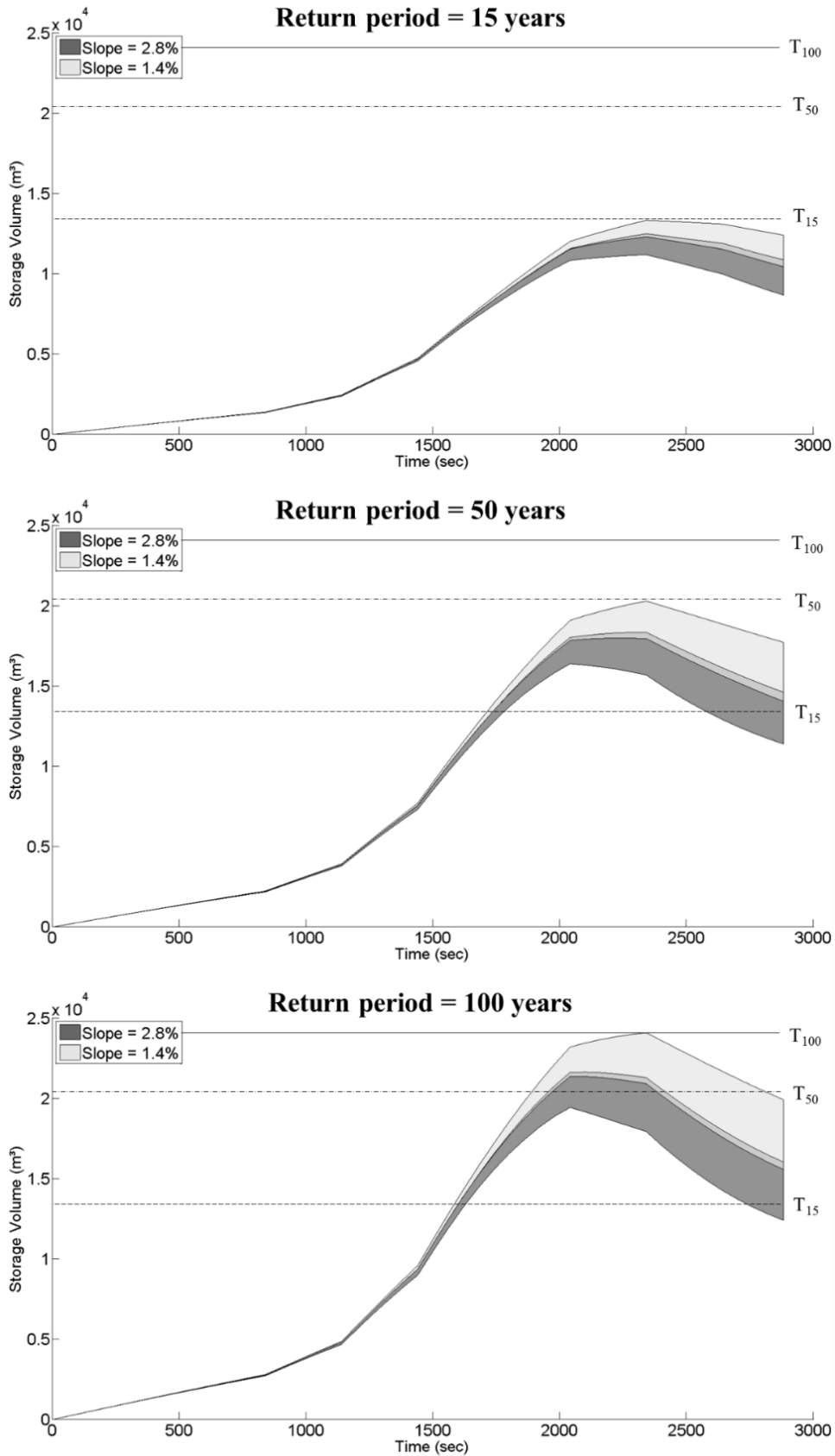
311 We first look at the variation of the flow variables when the urban form is varied, and we compare
 312 these variations to those induced by changing the return period of the considered storm or the ter-
 313 rain slope. The envelopes of the times series of stored volume in the urban district, outflow dis-
 314 charge and mean water depth are displayed in Figure 4, Figure 5 and Figure 6, respectively. These
 315 envelopes reflect the influence of the urban forms on the flow variables. The scatter plots in Figure
 316 7 summarize the influence of the urban form on the peak values of the three flow variables for the
 317 various return periods and terrain slopes. The same information is presented in the form of boxplots
 318 in Figure C.1 in Supplementary material C. The following observations can be made:

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- For the three considered flow variables (stored volume, outflow discharge and mean water depth), the width of the envelopes of the time series are not affected by a change in the terrain slope. In contrast, these envelopes become wider when the considered return period is increased (Figure 4 to Figure 6). This is also demonstrated by the scatter plots in Figure 7a-c, which show a trend with a slope steeper than the 1:1 line, corresponding hence to a wider range of variation along the *y*-axis (higher return periods) than along the *x*-axis (lowest return period). This confirms that the influence of the urban form is magnified in the case of more extreme rainfall events. In contrast, when the terrain slope is varied between 1.4 % and 2.8 %, the range of variation of the flow variables is neither substantially widened nor narrowed (Figure 7d-f).
 - For the three flow variables, the relative influence of the urban form changes over time; and it does so differently depending on the considered flow variable (Figure 4 to Figure 6). Indeed, in the case of the stored volume, the width of the envelopes gradually increases with time, whereas for the outflow discharge and mean water depth, the width of the envelope is maximum close to the peak and then it decreases during the recession limb.
 - Figure 4 reveals that the influence of the urban form on the time series of the stored volume in the urban district seems relatively lower than the influence of the terrain slope and of the considered return period. Indeed, this is shown by the fact that the envelopes corresponding to distinct terrain slopes and return periods hardly overlap over the whole rising limb and at the peak of the time series.
 - In the case of the outflow discharge (Figure 5), a limited overlap between the envelopes corresponding to distinct terrain slopes can be seen; but there is still no overlap between the results corresponding to different return periods (see also Figure C.1 in Supplementary material C). This suggests that the influence of the urban form is slightly stronger on the outflow discharge than on the time series of stored volume.

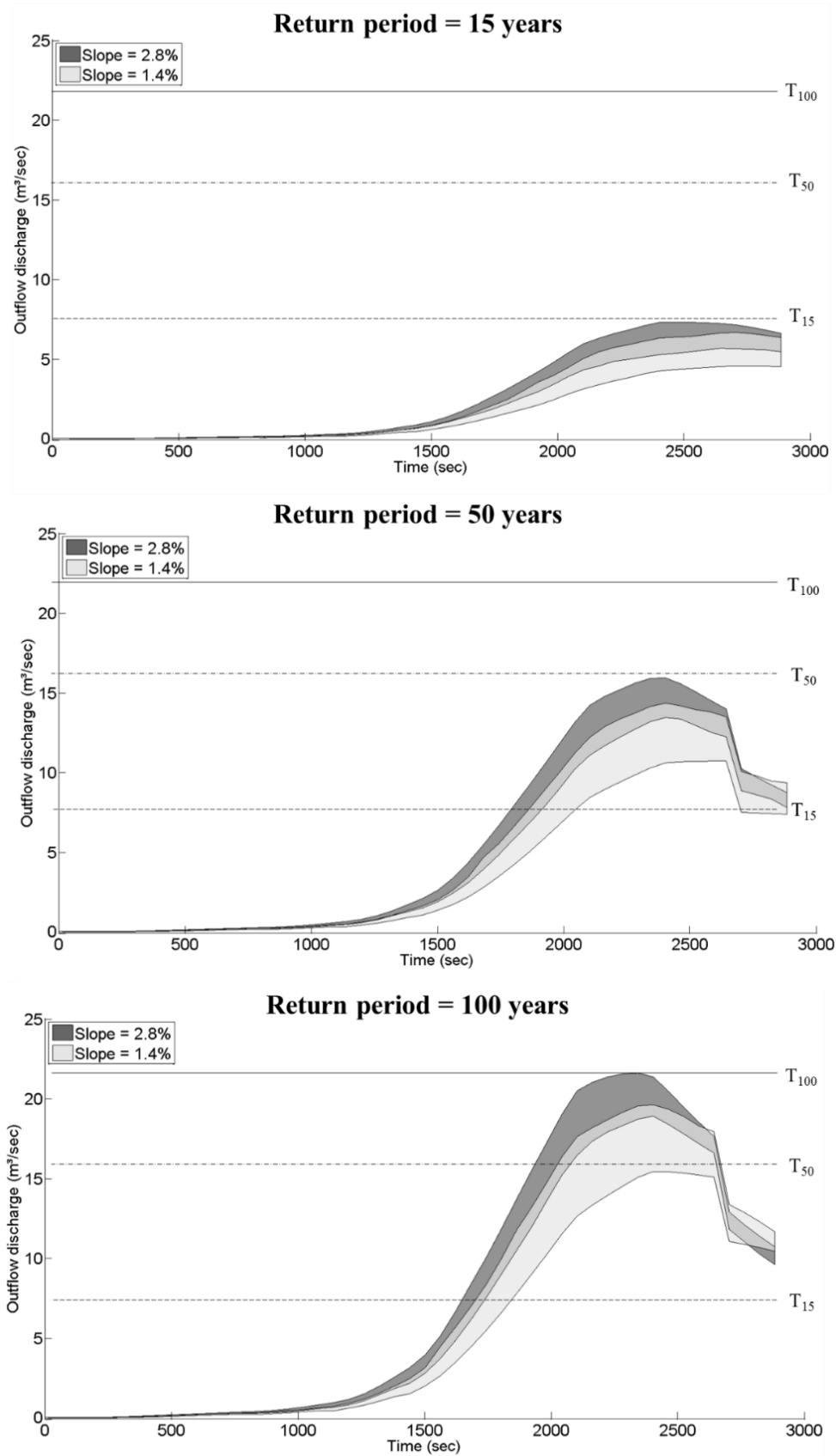
- 344 • For the peak values of these two flow variables, Figure 7a-b and d-e show that the ranges of
345 variation corresponding to distinct return periods do not overlap and that the overlaps remain
346 limited when the terrain slope is varied. This highlights that the considered changes in the re-
347 turn period and the tested terrain slopes have a stronger effect on the peak values of stored vol-
348 ume and outflow discharge than variations in the urban form.
- 349 • In contrast, for the times series of mean water depths in the urban district (of the order of 0.01
350 to 0.04 m), considerable overlaps are found between the envelopes corresponding to distinct
351 terrain slopes and return periods. This points at a relatively stronger influence of the urban
352 form on the mean water depth in the urban district than on the outflow discharge and stored
353 volume. Similarly, substantial overlaps are observed between the ranges of variation of the
354 peaks in water depth when the terrain slope is varied and, to a lesser extent, when the return
355 period is changed (Figure 7c and f).
- 356 • When the return period is increased, the rise in the peak outflow discharges is found twice to
357 three times larger than the rise in the stored volume or in the mean water depth, which change
358 with a similar magnitude, namely + 50 % between $T = 15$ years and $T = 50$ years in the present
359 case (Figure 7a-c).
- 360 • A steeper terrain slope leads to higher peaks in the outflow discharges and, conversely, lower
361 peaks in the stored volumes and mean water depths (Figure 7d-f). Again, the peaks in the out-
362 flow discharges vary more importantly with the terrain slope than the peaks in the stored vol-
363 umes and mean water depths (– 10 % in the present case).
- 364 • Finally, as clearly visible in the scatter plots in Figure 7, the results obtained for various return
365 periods and terrain slopes are strongly correlated. Pearson correlation coefficients are, respec-
366 tively, above 95 %, 91 % and 99.8 % for the stored volumes, the outflow discharges, and the
367 mean water depths. This implies that a more in-depth analysis of the influence of the urban
368 form conducted for a given return period or terrain slope, as performed in the next section, will

369 be essentially transferable to the other return periods and terrain slopes. This statement would
370 certainly not hold if infiltration processes were taken into account by the model.

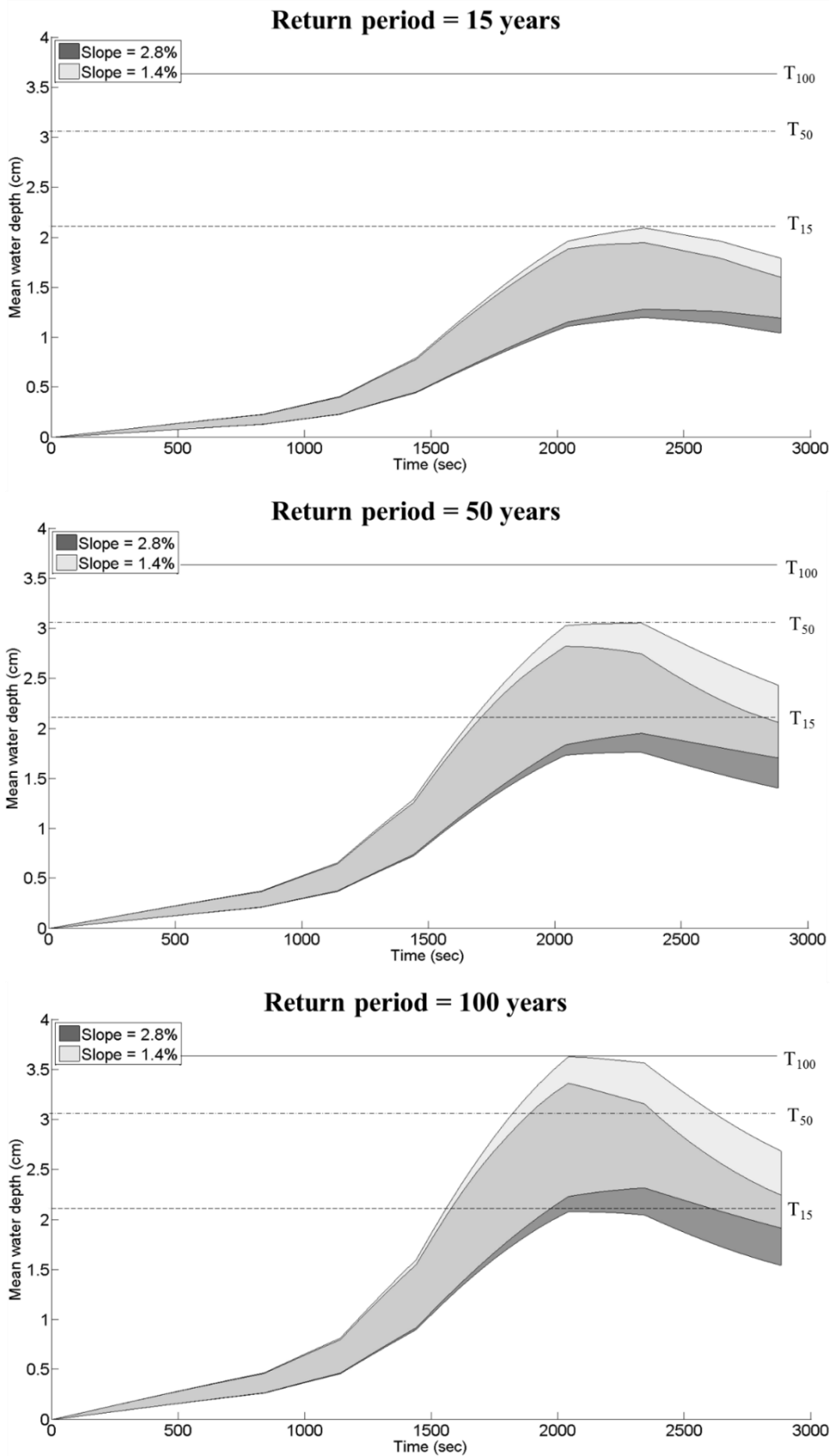
371 Note that here the urban forms basically do not influence the timing of the computed peak dis-
372 charges. However, if both pervious and impervious areas were considered in the simulations, de-
373 lays would occur in-between the peak discharges depending on where the impervious areas are
374 located.



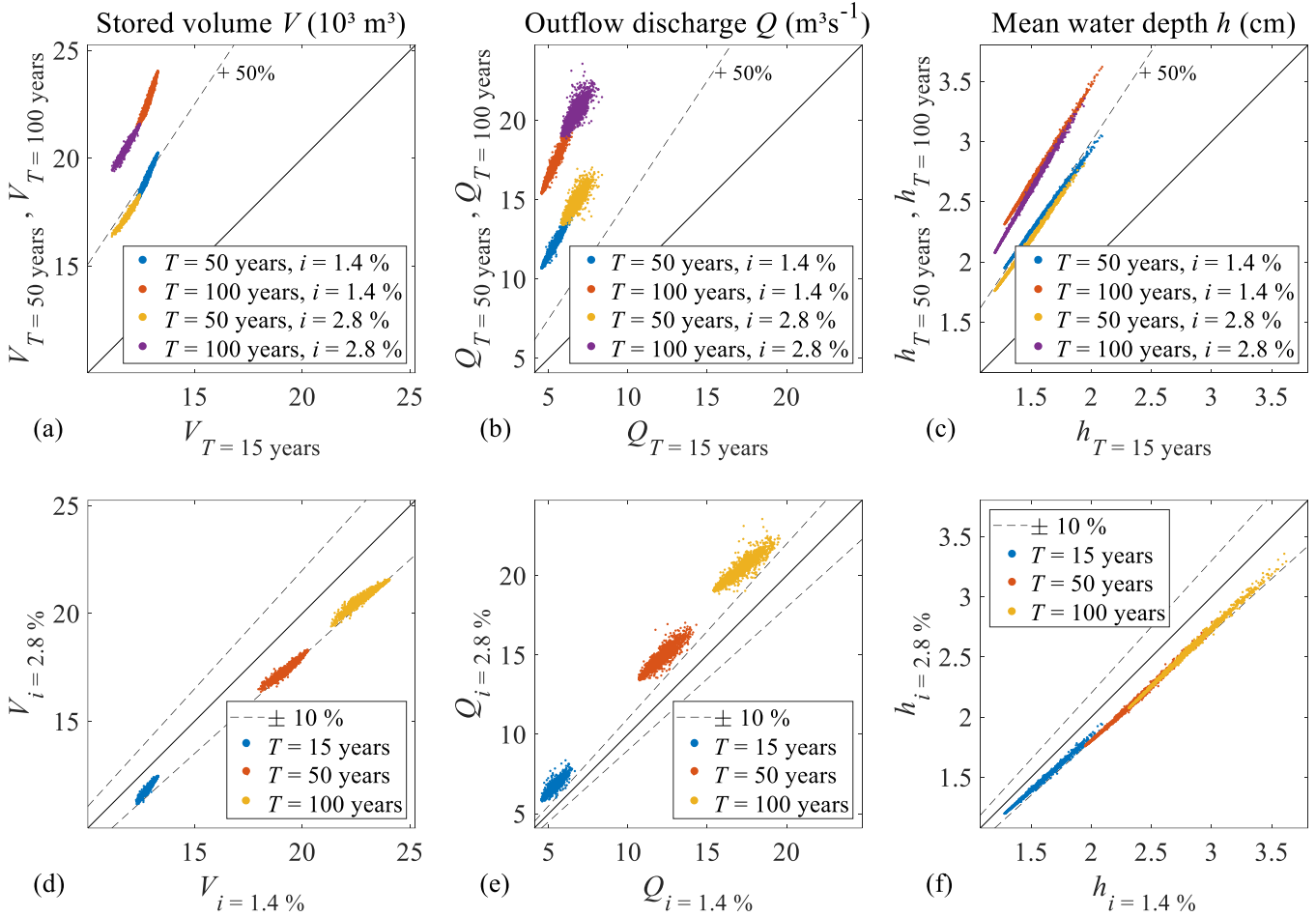
375
 376 Figure 4: Time evolution of the range of values of the stored volume over the 2,000 ur-
 377 ban forms. Note that the middle grey area corresponds to the area where the dark and
 378 light grey areas overlap.



379
 380 Figure 5: Time evolution of the range of values of the outflow discharge over the 2,000
 381 urban forms. Note that the middle grey area corresponds to the area where the dark and
 382 light grey areas overlap.



383
 384 Figure 6: Time evolution of the range of values of the mean water depth over the 2,000
 385 urban forms. Note that the middle grey area corresponds to the area where the dark and
 386 light grey areas overlap.



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Figure 7: Scatter plots indicating the influence of the return (a-c) period and the terrain slope (d-f) on the peak values of the flow variables: stored volume (a, d), outflow discharge (b, e) and mean water depth (c, f).

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3.2 Influencing urban parameters

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Among the 2,000 considered urban forms, we identified those which correspond to extreme values in the peaks of the three flow variables (i.e. maximum or minimum values of the peaks in the stored volumes, outflow discharges and mean water depths). This identification was performed independently for the two terrain slopes and the three return periods, but some urban forms lead to extreme peak values in more than one flow variable (Figure 8).

398 In Figure 9, we display the standardized values of the nine urban parameters x_i (Section 2.1) charac-
399 terising each of the urban forms leading to a minimum or a maximum in the peak values of the flow
400 variables. Figure 9 shows also a boxplot representing the whole sets of values of each urban param-
401 eter among the 2,000 considered urban forms.

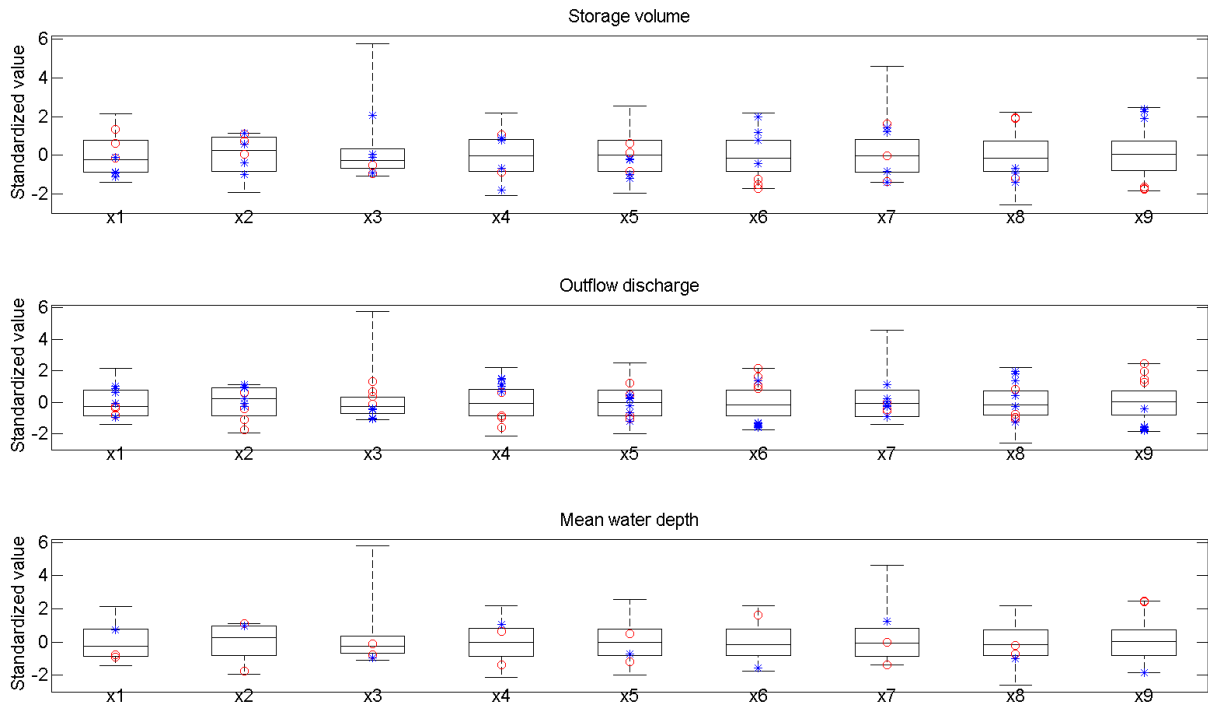
402 Figure 9 reveals that none of the urban parameters take consistently an extreme value (high or low)
403 in the configurations leading to extreme peak values in the flow variables; except for parameter x_6
404 (mean parcel area) and even to a greater extent for parameter x_9 (building coverage) for which this
405 is almost systematically the case. Indeed, maximum peak values of the storage volume (symbols \circ
406 in Figure 9) and minimum peak values of the outflow discharge and mean water depth (symbols $*$
407 in Figure 9) are consistently associated to low values of the building coverage x_9 . Conversely, mini-
408 mum peak values of the stored volume (symbols $*$ in Figure 9) and maximum peak values of the
409 outflow discharge and mean water depths (symbols \circ in Figure 9) correspond mainly to high values
410 of the building coverage x_9 . For the outflow discharge, all values of x_9 corresponding to extremes in
411 the peaks of this flow variable lie outside the 25th - 75th percentiles interval, at the exception of a
412 single case. For the two other flow variables, there is not a single exception. This hints at an over-
413 whelming influence of the building coverage x_9 in controlling the analysed flow variables during
414 urban pluvial flooding.



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417 Figure 8: Building footprints in the urban forms leading to the minimum peak values of the stor-
 418 age volume (a) and maximum peak values of the outflow discharge (b) and mean water depth (c)
 419 for the different terrain slopes i and return periods T .

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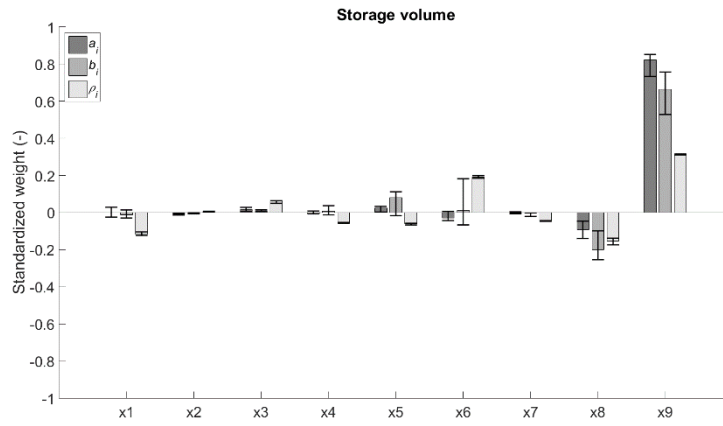
421
 422 Figure 9: Standardized values of the nine urban parameters corresponding to urban
 423 forms leading to extreme peak values of the three flow variables for the different terrain
 424 slopes and return periods (symbols \circ : maximum in peak value; symbols $*$: minimum in
 425 peak value). Boxplots represent the whole set of parameter values over the 2,000 urban
 426 forms. Note that symbols x_1 to x_9 are defined in Table 1.

427 The influence of the nine urban parameters on the flow variables was quantified using the statistical
 428 approaches presented in Section 2.3. The regression coefficients a_i and b_i (respectively without and
 429 with logarithmic transform) and the Pearson correlation coefficients ρ_i are shown in Figure 10. They
 430 were computed using all the results corresponding to the three return periods and the two terrain
 431 slopes. Error bars in Figure 10 indicate the range of variation of the coefficients obtained when indi-
 432 vidual combinations of return period and terrain slope are considered in the analysis (instead of
 433 combining all the configurations). For the outflow discharge and mean water depth, a positive value
 434 of a coefficient indicates that increasing the value of the corresponding urban parameter leads to a
 435 rise in the peak value of the flow variable. In contrast, a positive coefficient corresponds to an oppo-
 436 site variation in the case of the stored volume. This is due to the definition of the dependent variable
 437 y_1 , as detailed in section 2.3.

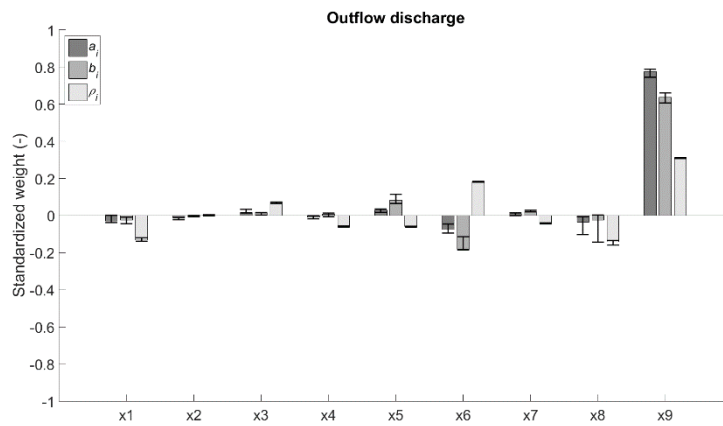
438 The results disclose the following:

- 439 • As inferred from previous results, the statistical analysis confirms the dominating influence of
440 the building coverage x_9 , which shows generally the coefficient with the largest magnitude.
441 The corresponding p -values are all virtually equal to zero, confirming the statistical signifi-
442 cance of this result. This means that raising the value of the building coverage reduces the
443 peak value of the stored volume, consequently to a reduction in the void area, and it increases
444 the peak values of the outflow discharges and mean water depths. This result is also high-
445 lighted by the scatter plots displayed in Supplementary material D.
- 446 • All coefficients associated to the urban parameters x_1 to x_5 and to x_7 remain consistently low in
447 magnitude, revealing a limited influence of these urban parameters on the studied flow varia-
448 bles.
- 449 • The variations in the coefficients associated to x_6 (mean parcel area) when the statistical ap-
450 proach is varied are explained by the existing positive correlation between parameters x_6 and
451 x_9 , as detailed in Bruwier et al. (2018). Indeed, when a statistical approach leads to a relatively
452 lower (resp. higher) coefficient for x_6 , it is compensated by a higher (resp. lower) value of the
453 coefficient associated to x_9 .
- 454 • Besides the building coverage, the second most influential urban parameter seems to be the
455 lateral setback x_8 , which is closely related to the distance between adjacent buildings. This is
456 particularly true for the stored volume and the outflow discharge. Indeed, increasing the side
457 setback enhances the connectivity between various parts of the urban area, hence enabling
458 more effective storage over the duration of the storm. The corresponding p -values are gener-
459 ally very close to zero and, at most of the order of 9×10^{-3} .

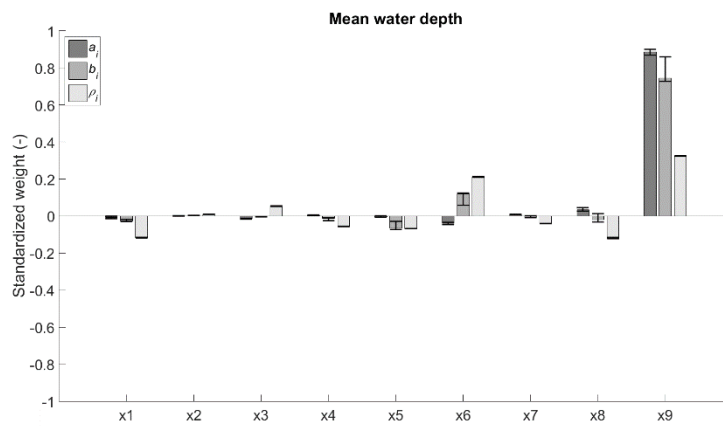
460 Overall, these results are to a great extent consistent with those obtained by Bruwier et al. (2018)
461 for river flooding. The main difference is that the dominating influence of the building coverage on
462 the flow variables is more severe for pluvial flooding than for river flooding.



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Figure 10: Comparison of regression coefficients a_i and b_i obtained from multiple linear regression respectively without and with logarithmic transform, and Pearson correlation coefficients ρ_i computed from computations over the six combinations of terrain slopes and return periods. Each set of coefficients are standardized so that the sum of the nine absolute values is one. Intervals gives the extreme values obtained for specific combinations of terrain slopes and return periods. Symbols x_1 to x_9 are defined in Table 1.

472 Since the analysis above is based on the mean water depth, it does not reflect explicitly the effect of
 473 urban forms on the spatial distribution of water depths. To address this, Supplementary material E
 474 looks at the effect of choosing alternate representative water depths (such as various percentiles).
 475 The results of the statistical analysis performed based on these alternate representative water depths
 476 reveal that the relative influence of the urban parameters remains essentially similar in all cases, so
 477 that the above conclusions still apply, particularly as regards the overwhelming influence of the
 478 building coverage (x_9).

479 3.3 Number of urban variables used in the statistical analysis

480 The statistical analysis presented in section 3.2 highlighted the dominant influence of the building
 481 coverage on the peak values of the flow variables compared to a configuration without buildings.
 482 Here, we compare the predictive capacity of regression models involving either the nine urban pa-
 483 rameters x_1 to x_9 or a subset of them (either the building side setback x_8 and the building coverage
 484 x_9 , or only the building coverage x_9). The capacity of each regression model to predict the peak
 485 value of flow variable j is evaluated through the error E_j computed as follows:

$$486 \quad E_j = \frac{\sum_{i=1}^N |y_{ij} - \hat{y}_{ij}|}{N y_{j,\text{mean}}} \quad (7)$$

487 where \hat{y}_{ij} is the predicted value of the peak flow variable y_{ij} corresponding to urban form i .

488 As shown in Table 2, the errors are minimum when all urban parameters are taken into account; but
 489 the errors increase only marginally if all parameters but x_9 , or x_8 and x_9 , are disregarded. Particularly
 490 for peaks in mean water depths, the error hardly changes when the regression model accounts only
 491 for x_9 , or x_8 and x_9 (increase in E_j by maximum 0.2 percentage points). This strengthens the claim
 492 that the considered flow variables are essentially controlled by the building coverage and, to a lower
 493 extent, by the lateral setbacks.

494 The results in Table 2 also highlight that, for the three flow variables, the error on the predicted
 495 peak values is lower with the logarithmic transform than without. This is consistent with the formu-
 496 lation of Eq. (6) which appears more physically sound than Eq. (5). Also, the peaks in mean water
 497 depths are predicted with a better accuracy ($E_j \approx 5\%$) than the peaks in stored volumes ($E_j \approx 12$ -
 498 13%) and in outflow discharges ($E_j \approx 16$ -17%). Note that the errors are evaluated in the untrans-
 499 formed space.

500 Table 3 shows the coefficients derived from a multiple linear regression model with logarithmic
 501 transform based on urban parameters x_8 and x_9 . The results emphasize the relatively lower influence
 502 of the lateral setback x_8 on the peak flow variables. The building coverage has a weight about one to
 503 two orders of magnitude larger than the lateral setback for the prediction of the peaks in stored vol-
 504 ume, outflow discharge and mean water depth. From the perspective of urban planning, this consid-
 505 erable difference in the weights hampers the compensation of an increased building coverage (i.e.
 506 urban development) by a “flood-sensitive” arrangement of the buildings (e.g. with higher lateral set-
 507 backs), since the latter effect remains by far smaller than the former one. This contrasts with the
 508 case of river flooding (Bruwier et al. 2018), where the relative influence of the building coverage
 509 and another composite indicator of the buildings arrangement differs only by a factor three, so that
 510 the detrimental impact of an increase in the building coverage (i.e. new developments) can be effec-
 511 tively mitigated by a suitable location of the buildings (Bruwier et al. 2018).

Urban parameters	Multiple linear regression (MLR): Eq. (5)			MLR with logarithmic transform: Eq. (6)		
	x_1 to x_9	x_8 and x_9	x_9	x_1 to x_9	x_8 and x_9	x_9
Stored volume	12.4%	12.6%	13.4%	11.7%	11.9%	13.4%
Outflow discharge	16.2%	17.0%	17.3%	16.1%	16.6%	17.1%
Mean water depth	7.2%	7.4%	7.4%	4.9%	5.0%	5.1%

513 Table 2: Error E on the predicted value of the peak flow variables using different sets of
 514 explanatory urban parameters and two linear regression models. Note that symbols x_1 to

515 x_9 are defined in Table 1.

$y_j = b_{0,j} x_8^{b_{8,j}} x_9^{b_{9,j}}$	$b_{8,j}$	$b_{9,j}$
Storage volume	-0.27	0.95
Outflow discharge	-0.19	1.1
Mean water depth	0.034	1.2

Table 3: Coefficients obtained from a linear regression with logarithmic transform accounting for the urban parameters x_8 and x_9 . Note that symbols x_1 to x_9 are defined in

Table 1.

4 CONCLUSION

In this study, previous research on the influence of the urban form on river flooding (Bruwier et al. 2018) was extended to the case of urban pluvial flooding. We have considered 2,000 synthetic arrangements of buildings, characterized by nine urban parameters (typical street orientation, curvature, length and width, mean parcel area, building setbacks, ...), and two different terrain slopes. For each of them, we computed surface flow variables using a validated hydro-inundation model forced by uniform rainfall input corresponding to design storms of various return periods. Our results show the following:

- variations in the urban forms has generally a more limited effect on the peak values of stored volume in the urban district and on the outflow discharge compared to changes in the storm return period or in the terrain slope;
- in contrast, a strong influence of the urban form was found on the mean water depths in the urban area;
- the influence of the urban form is magnified in the case of more extreme rainfall events, which hints at a growing importance of flood-sensitive urban planning as an adaptation to climate change;
- based on statistical analysis, we highlighted the overwhelming influence of the building coverage compared to other urban parameters;

- 537 • the distance between adjacent buildings is another influencing parameter, but to a lesser extent.

538 From the perspective of urban planning, the strongly dominating influence of the building coverage
539 seems to hamper the compensation of an increasing building coverage (i.e. urban development) by
540 means of a more “flood-sensitive” arrangement of the buildings (e.g. with higher lateral setbacks),
541 since the latter effect remains by far smaller than the former one. This result obtained here for plu-
542 vial flooding differs from earlier results obtained in the context of river flooding (Bruwier et al.
543 2018). Moreover, these conclusions appear robust with respect to changes in the terrain slope or in
544 the rainfall intensity.

545 This study is the first one to date to analyse systematically the influence of the urban form on urban
546 pluvial flooding. Nonetheless, given the high complexity of the actual interactions between urban
547 systems and flow processes, our work presents a number of limitations, which should be further an-
548 alysed in future research to pave the way for more flood-resilient urban planning. This includes an
549 improved representation of urban drainage systems, land-use heterogeneity (parks, gardens ...),
550 real-world topography (e.g. sinks), obstacles (Mignot et al. 2013), rooftops connectivity, and local
551 water management devices (water tanks, green roofs, storm basin ...), which all have a substantial
552 influence on urban pluvial flooding.

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