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1 Single Porosity Model: Exploring the Spatial Resolution  
2 Limits in Complex Urban Patterns

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5 **Abstract**

6 When modeling large-scale urban floods, the use of porosity non-linear shall-  
7 low water equations (PNSWE) emerges as an interesting sub-grid approach  
8 for reducing computation time while preserving the structure of the solu-  
9 tion. In such models, fine-scale topographic information is represented at  
10 a coarser scale through porosity parameters, enabling a speed-up in com-  
11 putations at the expense of losing accuracy while computing hydrodynamic  
12 variables. Porosity accounts for both the change in storage and exchange  
13 section due to the presence of obstacles (e.g., houses or buildings) in the  
14 floodplain and introduces a new source term associated with its gradient into  
15 the momentum equations. Here, we use the Single Porosity model (SP) in  
16 Cartesian coordinates to simulate flows in both an idealized and a real-world  
17 urban area, while gradually increasing the spatial resolution. During such  
18 partial coarsening, in which we move from fine- to macro-scale, the porosity  
19 distribution changes within the urban zone from a highly heterogeneous field

20 to a more uniform one. At an intermediate meso-scale, where the cell size is  
21 of the order of the street width and the reduction in computation time is still  
22 significant, the main preferential flow paths within the urban area can be  
23 captured by means of the porosity gradient. At such a scale, good agreement  
24 with refined classical model solutions is found for flow depth, flood extension,  
25 and hazard index, both in magnitude and spatial distribution. Numerical re-  
26 sults highlight the importance of porosity models for quickly assessing flow  
27 properties during an event and improving real-time decision-making through  
28 reliable information.

29 *Keywords:* urban floods, porosity shallow water equations, flood hazard,  
30 numerical modeling, Godunov-type schemes.

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## 31 **1. Introduction**

32 Floods stand as the world's most recurrent disaster, inflicting significant  
33 damage, casualties, and economic losses every year (Liu et al., 2018). Recent  
34 investigations have shown that between 1980 and 2020, more than 4800 flood  
35 disasters have occurred, resulting in an annual average of more than 5900  
36 deaths and \$21 billion USD in losses (Duan et al., 2022). These events have  
37 also been responsible for almost half of the human fatalities from natural  
38 hazards (Lee and Vink, 2015; FitzGerald et al., 2010).

39 Analyses of future flood risks and associated damages show that they  
40 will be strongly influenced by two critical factors: urbanization and climate  
41 change (Barría et al., 2019; Pariartha et al., 2023; Wang et al., 2023). As  
42 urbanization continues to accelerate, an increasing settlement of people in  
43 high-risk prone areas has led to a higher exposure of population and in-

44 frastructure to potential flooding events (Yari et al., 2019; Alderman et al.,  
45 2012; Jonkman and Vrijling, 2008). This has been exacerbated by improper  
46 land-use planning (Jha et al., 2012), rapid transitions in land-use that limit  
47 or prevent water infiltration in cities (Jodar-Abellan et al., 2019; Lee and  
48 Kim, 2018), and critical infrastructure near river channels exposed to scour  
49 in subcritical or supercritical conditions (Link et al., 2019; Nieto et al., 2023).

50 In addition, climate change-driven alterations in rainfall patterns and sea  
51 level rise, will affect the magnitude, frequency, and intensity of urban flood  
52 events, which are expected to increase continuously (IPCC, 2021; Jamali  
53 et al., 2018; Chen et al., 2021). Climate modifications are also expected to  
54 influence interannual variations associated to climatic oscillations, such as  
55 the El Niño Southern Oscillation (ENSO), which may induce strong spatio-  
56 temporal fluctuations in flood occurrences (Ward et al., 2014).

57 Flood risk assessment (FRA) is a critical feature for flood risk manage-  
58 ment and it plays an essential role in informing decision-making and the for-  
59 mulation of effective mitigation measures (Zou et al., 2013). Effective FRA  
60 approaches must be based on reliable estimates of flood hazards, exposure,  
61 and vulnerability. An important element of the first two components corre-  
62 sponds to the computation of the flow properties within urban areas, which  
63 define the magnitude of the event on-site (Bruwier et al., 2017). Therefore,  
64 the requirement to assess flood hazards needs precise modeling tools to eval-  
65 uate the propagation of floods in urban systems (Ferrari and Viero, 2020),  
66 making numerical models a vital component of FRA (Rosenzweig et al., 2021;  
67 Sanders et al., 2008).

68 The classical Nonlinear Shallow Water Equations (NSWE) or Saint-Venant

69 equations have been generally considered state-of-the-art for the simulation  
70 of inundations and flood paths, replacing one-dimensional former approaches  
71 (Costabile and Macchione, 2015). A main concern with such models is the  
72 extensive computational time required to numerically solve the system in  
73 difficult topographies with the necessary resolution in extensive urban areas,  
74 which can be in the order of centimeters (Bates, 2012; Özgen et al., 2016;  
75 Kim et al., 2015; Contreras and Escauriaza, 2020).

76 Performing a simple coarsening of structured meshes generally leads to  
77 large errors in flood predictions because it degrades the representation of  
78 buildings and other infrastructure (Yu and Lane, 2006; Brown et al., 2007).  
79 The fundamental issue is that computational meshes can only resolve features  
80 considerably larger than the grid size (Sanders et al., 2008). Thus, Porosity  
81 Nonlinear Shallow Water Equations (PNSWE) emerge as an interesting and  
82 consistent sub-grid approach for modeling urban floods, where the porosity  
83 accounts for both the change of the storage and exchange section due to the  
84 presence of buildings in the inundated areas (Dewals et al., 2021).

85 In models based on the PNSWE, fine-scale topographic information is  
86 represented at a coarser scale using porosity parameters, allowing a signif-  
87 icant decrease in computational time at the expense of losing accuracy in  
88 the calculation of hydrodynamic variables. The early approaches to PNSWE  
89 emerged in a differential formulation of the equations, like micro-topography  
90 sub-grid modeling (Defina et al., 1994). These early models inspired later  
91 developments focused on urban areas, such as the Single Porosity (SP) model  
92 (Guinot and Soares-Frazão, 2006). Building upon this, further advancements  
93 addressed urban terrain anisotropies, as seen in models such as the Multiple

94 Porosity (MP) model (Guinot, 2012) and the addition of a building drag  
95 formulation (Velickovic et al., 2017). Simultaneously, PNSWE models were  
96 developed based on integral formulations, primarily focused on represent-  
97 ing porosity using local geometric parameters. The pioneering work in this  
98 direction is the Integral Porosity (IP) model developed by Sanders et al.  
99 (2008). This model provided the foundation for the development of sub-  
100 sequent models, including the Dual Integral Porosity (DIP) model (Guinot  
101 et al., 2017), which aimed to overcome mesh-dependency issues associated  
102 with the IP model. Moreover, advancements such as incorporating depth-  
103 dependent porosity, as demonstrated in the Depth-Dependent Dual Integral  
104 Porosity (DD-DIP) model of Guinot et al. (2018), further enriched the inte-  
105 gral approach.

106 The SP model, based on the differential form of the equations, assigns a  
107 unique porosity value per cell for large-scale resolutions to maintain the par-  
108 simony of the formulation. This porosity, referred to as storage porosity ( $\phi$ ),  
109 corresponds to the fraction of the plan view area available to the flow, while  
110  $(1 - \phi)$  represents the fraction of the surface occupied by buildings. The SP  
111 model is particularly interesting since it retains mathematical properties of  
112 the classical NSWE model such as hyperbolicity, rotational invariance, and  
113 celerity of small disturbances (Varra et al., 2020). The first SP models as-  
114 sumed a single constant value of the porosity parameter for the cells within  
115 the urban area. The porosity is then computed at a large-scale level, con-  
116 sidering all the extent of the city, and then imposed on the cells within the  
117 urban domain, while the outer cells have an assigned value of  $\phi = 1$ . As a  
118 consequence, the source term involving the porosity parameter only accounts

119 for a local head loss at the entrance and exit of the urban area. The head  
120 losses occurring inside urban areas are commonly accounted for by using drag  
121 force-type of source terms (Soares-Frazao et al., 2018).

122 As pointed out by Sanders et al. (2008), the formulation of differential  
123 equations describing flow in porous media is accomplished by postulating the  
124 existence of a Representative Elementary Volume (REV), which is required  
125 for continuum purposes. The REV, now understood as a representative area  
126 rather than volume (used for consistency with previous published works),  
127 refers to an area large enough to capture average properties that can be  
128 represented as porosity in this case and thus characterizes the entire urban  
129 domain. Therefore, this uniform porosity value should be computed at the  
130 REV level.

131 Initial work on the definition of REV demonstrated that for typical Eu-  
132 ropean capital cities, a large grid size of at least 2.3 km is needed (Guinot,  
133 2012). In many situations, however, this size may exceed the spatial scale  
134 of the urban area itself, making the REV meaningless for small towns or ur-  
135 ban areas that are spatially limited. Practical applications of the PNSWE,  
136 however, have demonstrated the viability of finite-volume schemes for the  
137 solution of the SP model with a local storage porosity defined at the level of  
138 computational cells (Velickovic et al., 2010; Özgen et al., 2017; Soares-Frazao  
139 et al., 2018). In the same line, and as discussed by Guinot (2012), the exis-  
140 tence of the REV in the urban area has no consequences with respect to the  
141 applicability of the equations.

142 Numerical studies using porosity at the computational cell-level, which  
143 implies defining a non-uniform porosity distribution within the city, have im-

144 proved the results compared to the constant porosity value inside the urban  
145 domain (Soares-Frazao et al., 2018). In some approaches, the original poros-  
146 ity definition, applied to the cell-level, has been manipulated further in order  
147 to represent the city pattern and improve the flow depth estimation, like the  
148 building-peak distribution proposed by Linkens and Snaps (2017).

149 In this investigation we use the SP model within a Cartesian frame to solve  
150 the propagation of urban floods, employing the original storage porosity ( $\phi$ )  
151 definition at the computational cell-level, and evaluating the consequences of  
152 varying the size of the discretization. Motivated by the development of early-  
153 warning systems and faster-response models to analyze multiple potential  
154 scenarios before a extreme hydrometeorological event, the primary objective  
155 is to evaluate predictions of water depths, flood limits, and hazard index  
156 for various spatial resolutions, providing new insights on the advantages and  
157 limitations of this formulation.

158 It is also of special interest to understand the trade-offs between the re-  
159 duction of the computational time and the prediction error induced by the  
160 coarsening process. From this systematic procedure, we study the spatial res-  
161 olution limits for the SP model to deliver reliable results that can be trusted  
162 by decision makers and managers. This formulation can be implemented in  
163 early-warning systems that typically require a rapid response and the eval-  
164 uation of multiple potential scenarios, based on a physical framework and  
165 without relying only on machine learning approaches.

166 The model is applied in two cases: (i) An idealized non-periodic city; and  
167 (ii) A real-world case study located in La Reina, a district within the city  
168 of Santiago de Chile. A fine-scale well-balanced, widely validated NSWE



169 model, introduced by Guerra et al. (2014) is used for computing a reference  
170 solution (see also Loose et al., 2005). These high-resolution calculations  
171 provide detailed results (Contreras and Escauriaza, 2020), but they are highly  
172 time-consuming at the urban resolution obtained from LiDAR or satellite  
173 images. In our analysis, we systematically analyze the effects of downgrading  
174 the spatial resolution, incorporating the sub-grid effects through the PNSWE  
175 model.

176 This paper is organized as follows: In Section 2, we present the approach  
177 for the numerical modeling of urban flood, detailing the governing equations,  
178 the collection of numerical methods used in the calculation, and the mesh  
179 coarsening process. In Section 3, we describe the two different simulation  
180 cases and the mesh resolutions employed in each case. Section 4 provides  
181 numerical results and discussion of computational time, incorporating the  
182 analysis of the physical variables that define the event, such as the maximum  
183 depth, flood limits, and hazard estimation. Finally, in Section 5, we present  
184 the conclusions and closing remarks.

## 185 **2. Modeling Urban Floods with Porosity**

### 186 *2.1. Governing Equations*

187 The shallow water equations correspond to a simplification of the three-  
188 dimensional Navier-Stokes equations, where the main assumptions are: (i)  
189 incompressible and homogeneous fluid; (ii) hydrostatic pressure distribution;  
190 (iii) negligible vertical velocities; and (iv) vertically averaged horizontal ve-  
191 locities. When adding storage porosity to the classical model and using the  
192 differential form, we obtain the PNSWE. In matrix form, they are expressed

193 as follows:

$$\frac{\partial}{\partial t}(\phi Q) + \frac{\partial}{\partial x}(\phi F) + \frac{\partial}{\partial y}(\phi G) = S_B(Q) + S_F(Q) + S_P(Q), \quad (1)$$

194 with

$$\begin{aligned} Q &= \begin{pmatrix} h \\ hu \\ hv \end{pmatrix}; & F(Q) &= \begin{pmatrix} hu \\ hu^2 + \frac{gh^2}{2} \\ huv \end{pmatrix}; & G(Q) &= \begin{pmatrix} hv \\ huv \\ hv^2 + \frac{gh^2}{2} \end{pmatrix}; \\ S_B(Q) &= \begin{pmatrix} 0 \\ -gh \frac{\partial z_b}{\partial x} \\ -gh \frac{\partial z_b}{\partial y} \end{pmatrix}; & S_F(Q) &= \begin{pmatrix} 0 \\ -S_{fx} \\ -S_{fy} \end{pmatrix}; & S_P(Q) &= \begin{pmatrix} 0 \\ \frac{gh^2}{2} \frac{\partial \phi}{\partial x} \\ \frac{gh^2}{2} \frac{\partial \phi}{\partial y} \end{pmatrix}, \end{aligned} \quad (2)$$

195 where  $\phi$  is the storage porosity,  $h$  corresponds to the water depth,  $u$  and  $v$   
 196 are the depth-averaged flow velocities in the  $\hat{x}$  and  $\hat{y}$  Cartesian directions,  
 197 respectively,  $t$  indicates time,  $z_b$  is the bed elevation,  $g$  is the gravity acceler-  
 198 ation ( $9.81\text{m/s}^2$ ) and  $S_{fx}$  and  $S_{fy}$  correspond to the friction source term in  
 199 the  $\hat{x}$  and  $\hat{y}$  direction, respectively. Note that a distinction is made between  
 200 the source terms, where  $S_B(Q)$  accounts for the bed slope,  $S_F(Q)$  is the bed  
 201 and wall friction, and  $S_P(Q)$  is the porosity gradient, which appears when  
 202 adding the porosity term to the classical model.

## 203 2.2. Numerical Model

204 The numerical solution of the system of equations (1) is obtained by  
 205 implementing a second-order Godunov-type scheme, where time stepping is  
 206 performed by means of a four-stage Runge-Kutta scheme (Guerra et al.,  
 207 2014). For the resolution of the Riemann problem, we use the original SP

208 formulation, which follows a lateralized discretization for the pressure source  
 209 terms in the momentum flux. Therefore, the static equilibrium conditions  
 210 are satisfied even when the porosity is different on both sides of the interface  
 211 (Soares-Frazaio et al., 2018). The source term that accounts for friction ef-  
 212 fects is discretized using a time-splitting procedure. Thus, the state variable  
 213 updating involves two stages: one for considering the friction source term  
 214 and the other for addressing the hyperbolic effects.

215 On the first step, the semi-discrete formulation of the system results in:

$$\frac{d}{dt}(\phi Q) = S_F(Q). \quad (3)$$

216 Using Manning equation to parameterize flow resistance, and linearizing the  
 217 system with respect to the known time level  $n$ , leads to a system of ordinary  
 218 differential equations with an analytical solution (Soares-Frazaio et al., 2018).  
 219 With these updated velocities, the friction-modified variables are computed,  
 220 which serve as input for the next time step.

221 On the second step, the system to solve considers only the bottom slope  
 222 and porosity source term, leading to:

$$\frac{\partial}{\partial t}(\phi Q) + \frac{\partial}{\partial x}(\phi F) + \frac{\partial}{\partial y}(\phi G) = S_B(Q) + S_P(Q). \quad (4)$$

223 The finite-volume semi-discrete system can be written as follows,

$$\frac{d}{dt}(Q_{i,j}) = \frac{1}{\phi_{i,j}\Delta x_{i,j}}(\phi F_{i-1/2R,j} - \phi F_{i+1/2L,j}) + \frac{1}{\phi_{i,j}\Delta y_{i,j}}(\phi G_{i,j-1/2R} - \phi G_{i,j+1/2L}), \quad (5)$$

224 where  $\phi_{i,j}$  and  $Q_{i,j}$  are cell-centered values,  $\Delta x_{i,j}$  and  $\Delta y_{i,j}$  are the compu-  
 225 tational cell widths in the  $\hat{x}$  and  $\hat{y}$  directions, respectively, and  $\phi F$  and  $\phi G$

226 are the numerical fluxes obtained by solving the RP in the  $\hat{x}$  and  $\hat{y}$  direc-  
 227 tions, respectively. The sub-index  $i - 1/2$  denotes the cell's left-side interface,  
 228  $i + 1/2$  the right-side interface,  $j - 1/2$  the lower-side interface, and  $j + 1/2$  the  
 229 upper-side interface. The subscript  $L$  indicates the left-side of the interface  
 230 (lower-side in  $\hat{y}$ ), while  $R$  indicates the right-side (upper-side in  $\hat{y}$ ).

231 In the initial part of this step, and with the aim of achieving a second-  
 232 order accurate discretization, a MUSCL reconstruction is performed for the  
 233 primitive variables  $h$ ,  $u$ ,  $v$ , and  $\eta$ , the last one being the free-surface elevation  
 234 ( $\eta = z_b + h$ ), using the *minmod* slope limiter. Subsequently, the RP is solved  
 235 with an HLL-modified solver, which accounts for a specific treatment for the  
 236 continuity and momentum equations. The source terms  $S_B(Q)$  and  $S_P(Q)$   
 237 discretizations are included in the Riemann solver; therefore, their effect is  
 238 accounted for through the fluxes  $\phi F$  and  $\phi G$ .

239 The two-dimensional CFL condition is used to calculate the time step  
 240 while ensuring numerical stability, the same stability criterion used for the  
 241 classical models, as the celerity of the waves is not affected by the inclusion  
 242 of a single porosity value per cell. The time step is computed as:

$$\Delta t^n = \frac{\min(\Delta x_{i,j}, \Delta y_{i,j})}{\max(\max(u_{i,j}^n + \sqrt{gh_{i,j}^n}, v_{i,j}^n + \sqrt{gh_{i,j}^n}))} \cdot \text{CFL}. \quad (6)$$

### 243 2.3. Meshing: From fine- to macro-scale

244 When modeling urban floods, we distinguish among three different mod-  
 245 eling spatial scales (Bruwier et al., 2017):

- 246 • Fine-scale: all obstacles in urban areas are resolved explicitly and with  
 247 a fairly good accuracy (about ten cells over the typical width of flow  
 248 paths).

- 249 • Meso-scale: the obstacles are explicitly represented in the computa-  
250 tional domain, but poorly resolved (just a couple of cells over the typ-  
251 ical width of flow paths).
- 252 • Macro-scale: the obstacles have a typical size comparable or smaller  
253 than the mesh size (flow paths are generally smaller than the size of a  
254 single computational cell).

255 For the reference solution computed with the classical NSW, we use fine-  
256 scale modeling. In an initial step, we treat the bare-earth topography and  
257 the buildings separately. For the bare-earth topography, we use a Digital  
258 Terrain Model (DTM), which is commonly obtained by means of LiDAR  
259 measurements. To account for the effects of the buildings on the flow, we use  
260 the Building-Block (BB) representation, where the bed elevation is artificially  
261 increased in the area where a building is situated. By setting an artificially  
262 high elevation, large enough to ensure that no water overflows the buildings,  
263 the flood would only flow around them. Such information about the location  
264 of the buildings is provided by the Binary Buildings Map (BBM). The BBM  
265 corresponds to the field built from the discrete binary variable  $B(i, j)$ , where  
266  $B(i, j) = 1$  indicates a void or street, while  $B_{i,j} = 0$  denotes a building. The  
267 geometry of the BB domain is therefore obtained by combining the BBM  
268 and the DTM.

269 For the SP model meshing, the structured fine-scale mesh is coarsened  
270 by merging neighboring cells (in an equal number of rows and columns). In  
271 such a way, the porosity at the computational cell-level for a coarse cell  $(i, j)$   
272 that contains  $W$  fine cells merged is computed from the BBM as

$$\phi_{i,j} = \frac{\sum_{w \in W} [(B)_w \cdot (A)_w]}{\sum_{w \in W} (A)_w}, \quad (7)$$

273 where  $A_w$  corresponds to the area of the  $w$ th merged cell. Note that the  
 274 original definition of storage porosity  $\phi$  is preserved at the cell-level. Similarly  
 275 to porosity, the resulting coarse terrain elevation is computed as:

$$(z_b)_{i,j} = \frac{\sum_{w \in W} [(z_b)_w \cdot (A)_w]}{\sum_{w \in W} (A)_w}. \quad (8)$$

276 Since we are working within a Cartesian reference frame and from a prac-  
 277 tical point of view, topography coarsening consists of DTM space averaging,  
 278 while porosity computation consists of BBM space averaging.

### 279 3. Simulations Cases

280 In this section, we briefly summarize the two cases analyzed in this in-  
 281 vestigation. We first study the performance of the SP model in an idealized  
 282 small domain, which is designed with a constant slope and a non-symmetric  
 283 heterogeneous distribution of buildings. In this first case the streets are  
 284 aligned in the same direction and perpendicular to the main flow, which is  
 285 used to test the performance of the model under different grid sizes without  
 286 the interference of other factors. In the second case, we apply the model to  
 287 real conditions in a densely populated urban area, which shows the ability of  
 288 the model to capture the flood propagation at different scales in a complex  
 289 urban geometry.

290 *3.1. Case 1: Idealized non-periodic case*

291 An idealized non-periodic urban area, where only right-angle corners are  
292 considered, is used to evaluate the performance of the model in a simplified  
293 distribution. The urban zone, presented in Figure 1(a), incorporates diverse  
294 building shapes and sizes, a typical Street Width (SW) of 9m, and voids  
295 representing parks or open areas. A constant slope of  $-0.573^\circ$  is also imposed  
296 in the direction of the flow.

297 To evaluate the model performance in this case, we carry out simulations  
298 considering a dam-break flow introduced in the direction of the arrow shown  
299 in Figure 1, which is the most severe condition that can be tested in these  
300 urban-like domains. For the remaining downstream boundaries, a free-exit  
301 condition is defined (Guerra et al., 2014). As an initial condition, the dam  
302 has 1m of water depth, while a dry-bed is used for the rest of the domain.

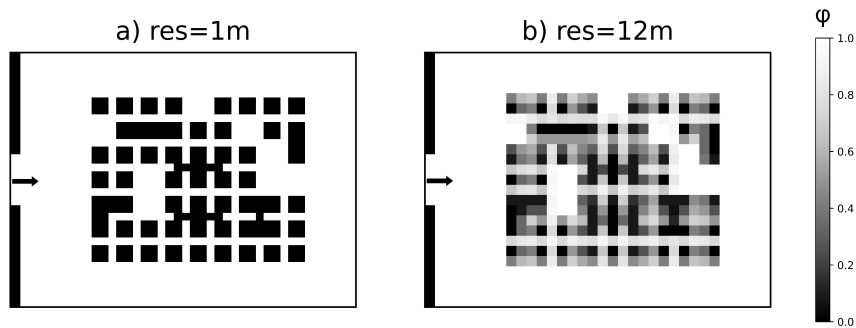


Figure 1: Idealized urban domain, with orthogonal street distribution, aligned with the main flow. The images show the maximum resolution of 1m (a), and the downgraded spatial grid with a size of 12m (b).

303 The fine-scale mesh has a resolution of 1m in order to have at least 9  
304 cells over the typical width of the flow paths, fitting the fine-scale definition.

305 For the partial transition to the macro-scale, we use the following resolutions  
306 (in meters): 2, 3, 4, 6, and 12. In the case of res=12m where the porosity  
307 map is shown in Figure 1b), the cell size is larger than SW, thus fitting the  
308 macro-scale definition.

### 309 *3.2. Case 2: La Reina, Santiago de Chile*

310 La Reina is a district situated in the Metropolitan area of Santiago, Chile,  
311 on the eastern border of the city. On this edge, and as shown in Figure 2, it  
312 limits with the Andean foothills, specifically with the Quebrada de Ramón  
313 basin, in which the main channel flows directly into the urban district (see  
314 Contreras and Escauriaza, 2020, for details). During May 1993, one of the  
315 most significant flood event recorded in this area occurred, triggered by a  
316 warm storm associated with the ENSO phenomenon (Garreaud, 1996), that  
317 elevated the 0°C isotherm up to 4000m masl (Contreras and Escauriaza,  
318 2020).

319 These conditions generated high-altitude heavy rainfall in the Andes  
320 mountains, and as a consequence, a substantial debris flow rapidly inun-  
321 dated the district in a matter of minutes. The event caused the unfortunate  
322 loss of 26 lives, 8 missing people, and major infrastructural damage, with a  
323 total financial cost of \$5 USD million. The reported affected area is shown  
324 in Figure 2 (Naranjo and Varela, 1996), denoted by a yellow marking.

325 We perform numerical simulations in this urban section, with a compu-  
326 tational domain that covers the green area of the urban zone, as shown also  
327 in Figure 2. For the topography, a 1m resolution DTM of the area is used,  
328 obtained through LiDAR sensing. Using data from OpenStreetMap (OSM),  
329 the BBM is built by subtracting the streets and park areas from the resi-



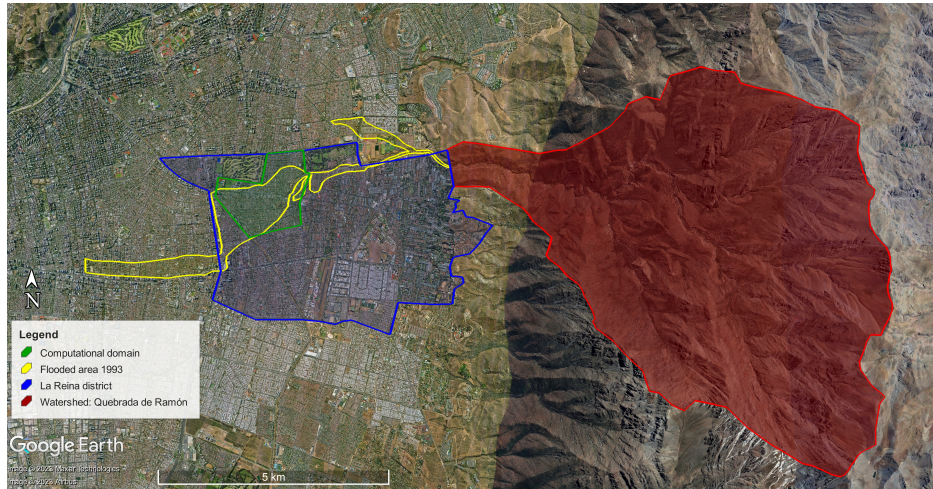


Figure 2: Quebrada de Ramón watershed in red. The yellow shaded marks the total inundated area of the 1993 event, and in green the section considered in this investigation (Data from Google Earth (c)).

330 denial area. With this procedure, and from a practical perspective, we are  
 331 assuming that everything that is not a street or park is a building. Thus, the  
 332 characteristic SW corresponds to 14m for common streets, while for main  
 333 streets, SW corresponds to approximately 30m.

334 The DTM indicates a mean slope of around  $-1^\circ$  in the E-W direction and  
 335  $-0.65^\circ$  in the N-S direction. A dam-break flow is introduced in the area  
 336 where the channelized stream overflows, according to previous simulations  
 337 from Contreras et al. (2020), following the direction indicated in Figure 3.  
 338 For the remaining downstream boundaries, a free-exit condition is defined.

339 As initial condition, the dam also has 1m of water depth, while a dry-bed  
 340 is used for the rest of the domain. Since the refined mesh resolution is 1m,  
 341 we have at least 14 cells over the width of the flowpaths, adjusting to the  
 342 fine-scale definition. For the partial transition to the macro-scale, we use the



Figure 3: Computational domain for flood simulations in La Reina district. (a) Street distribution in the real urban area at a resolution of 1m; (b) Downgraded domain at a resolution of 32m.

343 following resolutions (in meters): 4, 8, 12, 32, and 64. The porosity field for  
 344 res=32m is shown in Figure 3b).

## 345 4. Results and Discussion

### 346 4.1. Computational Time

347 Here we compare the CPU time of the reference model with the SP model  
 348 at different spatial resolutions to quantify the computational advantage of SP.  
 349 For case 1, shown in Table 1, a significant reduction is achieved when using  
 350 the SP model, which is even more considerable for higher spatial resolutions.  
 351 The percentages of CPU time, with respect to the reference model, vary  
 352 between 12% for a resolution of 2m and 0.1% for a resolution of 12m.

353 For case 2, where the CPU times are shown in Table 2, there is also a  
 354 notable reduction in computation time. When using a resolution of 4m, the  
 355 CPU time is around 16% with respect to the reference model. This reduction

Table 1: Computational times and averaged time-step for case 1 at different spatial resolutions.

Model	Resolution [m]	CPU time [s]	%CPU time	Mean $\Delta t$ [s]
<b>NSWE</b>	<b>1</b>	<b>1246</b>	<b>100%</b>	<b>0.2</b>
SP	2	152	12.4%	0.27
SP	3	55	4.2%	0.39
SP	4	25.5	2.2%	0.5
SP	6	9.6	0.7%	0.66
SP	12	1.7	0.1%	1.54

356 becomes more noticeable when using higher resolutions, reaching a CPU time  
 357 of 0.04% for the 64m resolution.

358 We can understand the reduction in time when using the SP model as  
 359 a combined effect of two factors. First, by using higher spatial resolutions  
 360 for the same domain, we have fewer cells and, therefore, fewer interfaces  
 361 of the discretization where the Riemann problem has to be solved. This  
 362 effect always yields a time reduction when increasing spatial resolution. In  
 363 addition, the time-step is less constrained by the cell dimensions according  
 364 to the stability condition stated in equation (6) as the area per cell is larger.

365 However, it is important to keep in mind that when using coarse grids  
 366 with the SP model, there is a tendency to overestimate velocities within the  
 367 urban domain. This generates the opposite effect, decreasing the time-step.  
 368 Thus, it is not possible to know a priori the effect of mesh resolution over  
 369 the time-step.

370 For case 1, we observe a clear tendency to increase the mean  $\Delta t$  with

Table 2: Computational times and averaged time-step for case 2 at different spatial resolutions.

Model	Resolution [m]	CPU time [s]	%CPU time	Mean $\Delta t$ [s]
<b>NSWE</b>	<b>1</b>	<b>130911</b>	<b>100%</b>	<b>0.002</b>
SP	4	21294	16.27%	0.18
SP	8	6580	5.03%	0.172
SP	16	1325	1.01%	0.122
SP	32	97	0.07%	0.410
SP	64	15	0.04%	0.105

371 spatial resolution. In this way, both effects act in the same direction to  
 372 reduce the total computational time.

373 For case 2, we note that, even when all values of the mean  $\Delta t$  of SP are  
 374 greater than the one from the reference model, there is not a clear tendency  
 375 with respect to the mesh resolution. For example, when comparing the 32m  
 376 with the 64m resolution, we notice that the former has a mean  $\Delta t$  around  
 377 4 times larger, but still presents a reduced total time with respect to the  
 378 latter. This suggests that the effect of computing less Riemann problems  
 379 at interfaces is more relevant.

380 Finally, it is important to consider that the time reduction achieved  
 381 through increased spatial resolution must be evaluated along with the er-  
 382 ror induced by the SP model. Although further time reduction is achievable  
 383 with coarser meshes, it is crucial to be aware that the hydrodynamic variables  
 384 lose physical meaning, as we discuss in the following subsection.

385 *4.2. Maximum water depth*

386 Here we compute the maximum water depth field through the total sim-  
 387 ulation time for each spatial resolution in the streets. With the objective of  
 388 having an overview of the mean induced error, we compute the Mean Abso-  
 389 lute Error (MAE). Also, we consider the Mean Bias Error (MBE) in order to  
 390 assess the systematic bias of the depth estimation in terms of underestimation  
 391 or overestimation.

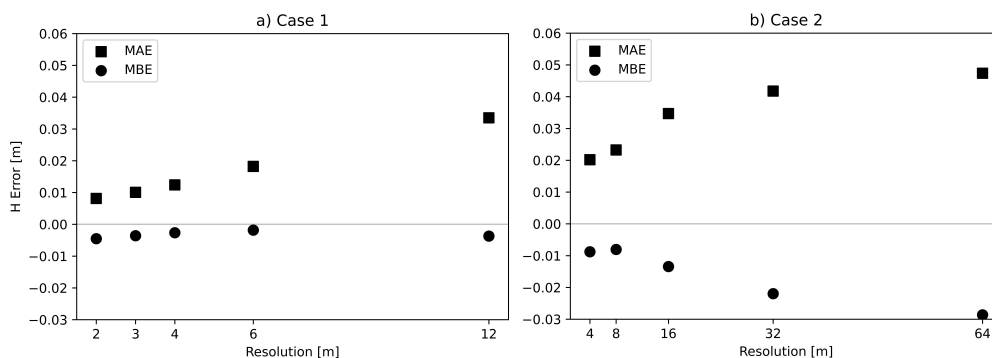


Figure 4: Comparison of the Mean Absolute Error (MAE) and Mean Bias Error (MBE) for the single porosity (SP) model in the two studied cases for different spatial resolutions.

392 In Figure 4, we observe a general trend of increasing MAE with the mesh  
 393 resolution that can be anticipated due to the topographic detail degradation.  
 394 The MBE indicates a systematic underestimation of the maximum water  
 395 depth in the streets. This suggests that the SP model has a more diffusive  
 396 character when the mesh size increases. Such results can be explained since  
 397 in the SP model obstacles lose their representation as the mesh size increases,  
 398 the water spreads over a larger area and converges to a lower water depth. As  
 399 a consequence, when considering only the flow in the streets, a lower water

400 depth is found.

401 In spite of these apparent shortcomings, the MAE remains below 4cm for  
402 the 12m resolution in case 1, while for case 2, it remains under 5cm when  
403 using a 64m mesh. The systematic underestimation in the streets is always  
404 less than 1cm on average for case 1. For case 2, the underestimation increases  
405 with mesh resolution, presenting an average underestimation of up to 3cm for  
406 a 64m resolution mesh. In both cases, the errors presented are on the order  
407 of a few centimeters for the maximum water depth, which are remarkable  
408 results in the context of a drastic change in spatial resolution.

409 It is important to consider not only the numerical averages but also the  
410 spatial distribution of the flood within the city. For instance, we could think  
411 that using a 64m grid and having an average underestimation of 3cm is an  
412 encouraging result for La Reina in case 2, even more so when considering the  
413 reduced computational time of the SP model option. However, as we will  
414 analyze in the following section, the model may lose its physical coherence  
415 when a very coarse resolution is employed.

#### 416 *4.3. Flood Extension*

417 With the objective of analyzing the spatial distribution of the flood, we  
418 compute the inundated region limits for a threshold of 0.1m. For the case 1,  
419 the flood map shown in Figure 5, demonstrates that the inundation pattern  
420 is captured, especially up to a resolution of 6m. Note that the flood pattern  
421 from the reference is represented for all SP resolutions below street width,  
422 which is 9m in this case.

423 Here, the effect of the resolution on the development of a shallower and  
424 more extended flow is well illustrated (e.g., while comparing 5a) with 5f)),

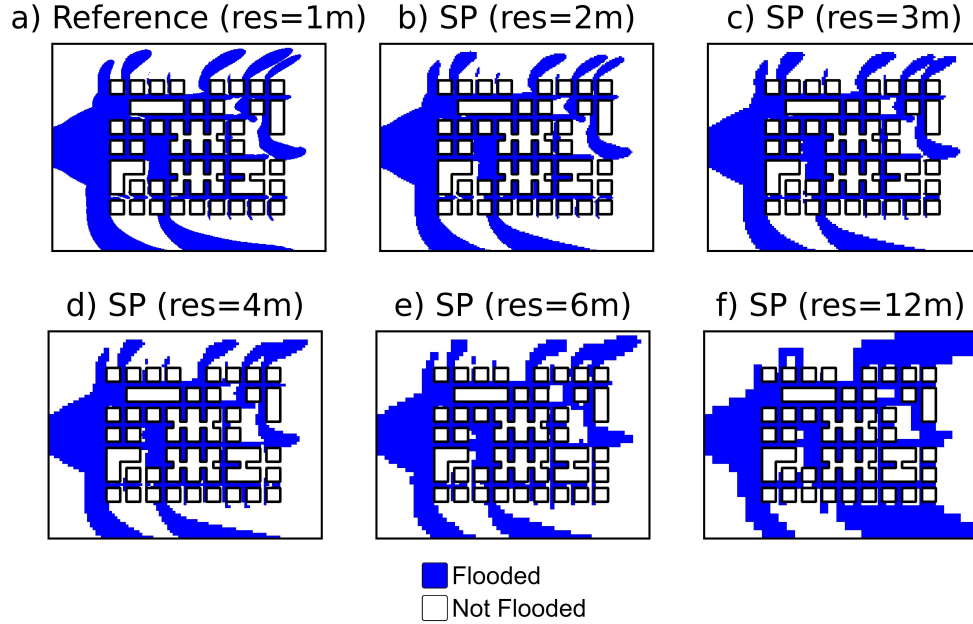


Figure 5: Flooded area for case 1 for different resolutions shows that at least for 6 times the size of the original mesh, the SP models captures with good agreement the inundated region.

425 suggesting again that the SP model has a more diffusive behavior.

426 In Figure 6 we show the flood map in the real urban area with an arbitrary  
 427 orientation of the streets. The simulation evidences problems with the  
 428 flow directionality induced by the SP model. In the fine-scale simulation in  
 429 Figure 6a), the north section of the urban zone became flooded, despite the  
 430 topography showing steeper slopes in other directions. This finding strongly  
 431 suggests that the flooding in that area was influenced by the presence of  
 432 preferential flow paths induced by the orientation of the streets. In contrast,  
 433 for the coarser mesh of 64m in Figure 6f), the flooding pattern follows the

434 bottom slope, largely ignoring the preferential flow paths induced by streets.  
 435 For intermediate cases, and specially for the 4m and 8m resolutions, where  
 436 the porosity gradient becomes more relevant, it can be seen that such direc-  
 437 tionality is partially recovered.

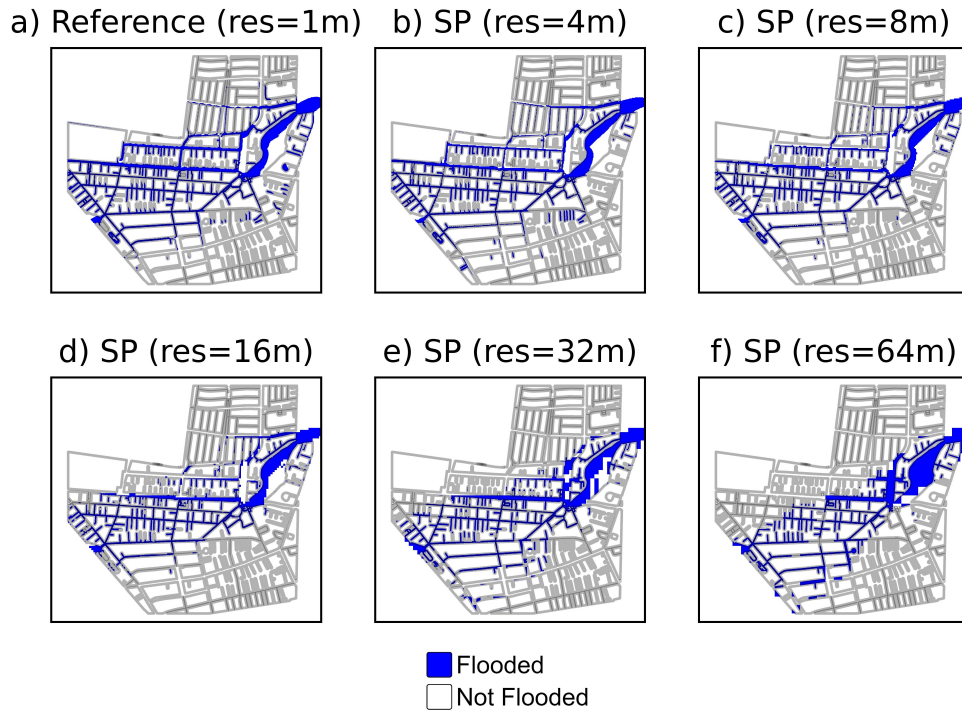


Figure 6: Flooded area for case 2 for different spatial resolutions. Grid sizes larger than the street width fail to reproduce the inundated area.

438 These results suggest that, similarly to case 1, for resolution values below  
 439 SW (14m in this case), the flood patterns can be successfully captured in  
 440 general terms.

441 A more detailed view of the mentioned north section is shown in Figure 7,  
 442 where the color green indicates a prediction agreement with the refined case,



443 red corresponds to an underprediction from SP, and blue an overprediction.  
 444 In this analysis is clear that for the cases with resolution below SW, the SP  
 445 model systematically fails to capture the inundation area. This seems to be  
 446 in agreement with the fact that the mesh manages to resolve features that  
 447 are larger compared to the cell size.

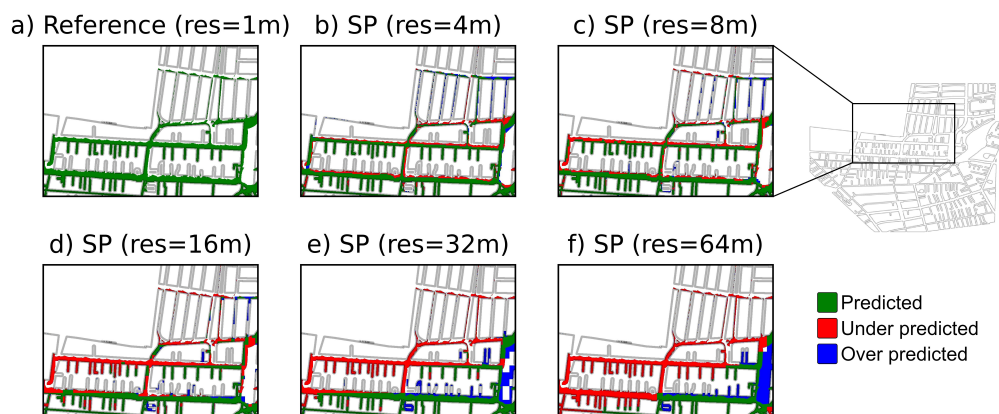


Figure 7: Flooded area for case 1 for different resolutions shows that at least for 6 times the size of the original mesh, the SP models captures with good agreement the inundated region.

#### 448 4.4. Hazard Index

449 For conducting a correct FRA, in addition to a thorough vulnerability  
 450 analysis, it is crucial to identify and correctly estimate the current and pos-  
 451 sible areas exposed to flood hazards (Erena et al., 2018). Thus, flood hazard  
 452 maps can be used to effectively reduce associated damage (Ogato et al.,  
 453 2020). For computing flood hazards, we use criteria based on the maximum  
 454 water depth and flow velocity, as proposed by Garcia and Lopez (2005).

455 Three hazard categories are defined based on conditions for both  $h$  and  
 456  $q = h\sqrt{u^2 + v^2}$  as: (i) Low for  $0.1\text{m} < h < 0.5\text{m} \wedge 0.1\text{m}^2/\text{s} < q < 0.5\text{m}^2/\text{s}$ ;  
 457 (ii) Medium for  $0.5\text{m} < h < 1.5\text{m} \vee 0.5\text{m}^2/\text{s} < q < 1.5\text{m}^2/\text{s}$ , and (iii) High  
 458 for  $h > 1.5\text{m} \vee q > 1.5\text{m}^2/\text{s}$ .

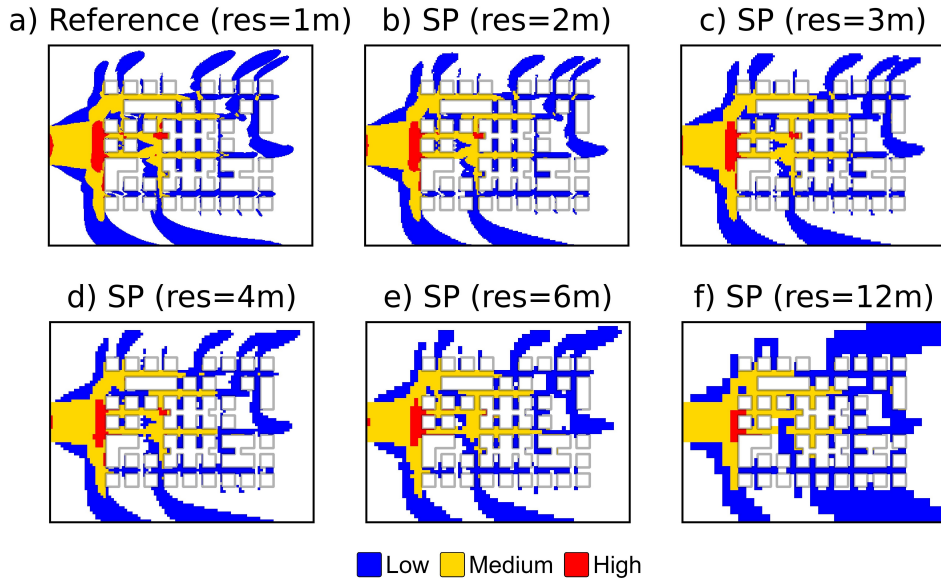


Figure 8: Hazard regions for case 1 according to the classification by Garcia and Lopez (2005). The systematic coarsening of the grid shows that most of the high-resolution characteristics are preserved up to the resolution of 6m.

459 The hazard map for case 1 in Figure 8 shows that the main structure  
 460 of the Low hazard area is well captured up to a 6m resolution. We can  
 461 see that the plumes leaving the urban area from the sides are also captured  
 462 at this resolution. For the case of 12m resolution, there is a significant  
 463 overestimation of the flooded area in the urban zone surroundings, especially  
 464 in the lateral boundaries near the downstream exit. For the Medium hazard

465 area, we can see in the reference model three main branches entering the city  
466 along the main flow-aligned streets and one deviated branch to the city front  
467 limit. Such branches are captured at all scales, where the 12m model fails  
468 to predict some minor areas inside the urban domain. For the High hazard  
469 areas, in red, we identify three locations from the reference: in the flow inlet,  
470 in the section of the urban area directly exposed to the flow, and in the  
471 center at a dead-end street. Only the section facing the dam-break flow is  
472 consistently captured for all resolutions, while the other zones are captured  
473 up to a 4m resolution. Overall, the main structure of the hazard zones  
474 and their spatial distribution are in good agreement with the high-resolution  
475 reference case up to a 6m resolution.

476 For case 2, shown in Figure 9, we observe a clear tendency to underesti-  
477 mate the hazard by the SP model. When using a 4m or 8m resolution, the  
478 general location of hazard zones is captured, but many streets in the Medium  
479 hazard category are estimated as Low hazard with SP. For narrower streets,  
480 a High hazard level is found in the refined model because of increased flow  
481 velocities, which are captured with SP until a 16m resolution. However, for  
482 resolutions from 16m and beyond, as preferential flow paths are not cap-  
483 tured, there are many zones with no hazard estimated. Thus, the inability of  
484 SP to accurately capture these paths directly affects the hazard assessment,  
485 evidencing major discrepancies with the refined model. Here it is very clear,  
486 observing the 32m and 64m resolutions, that the flood advances conforming  
487 to the bed slope as the resolution is increased, making the hazard map lose  
488 its physical meaning.

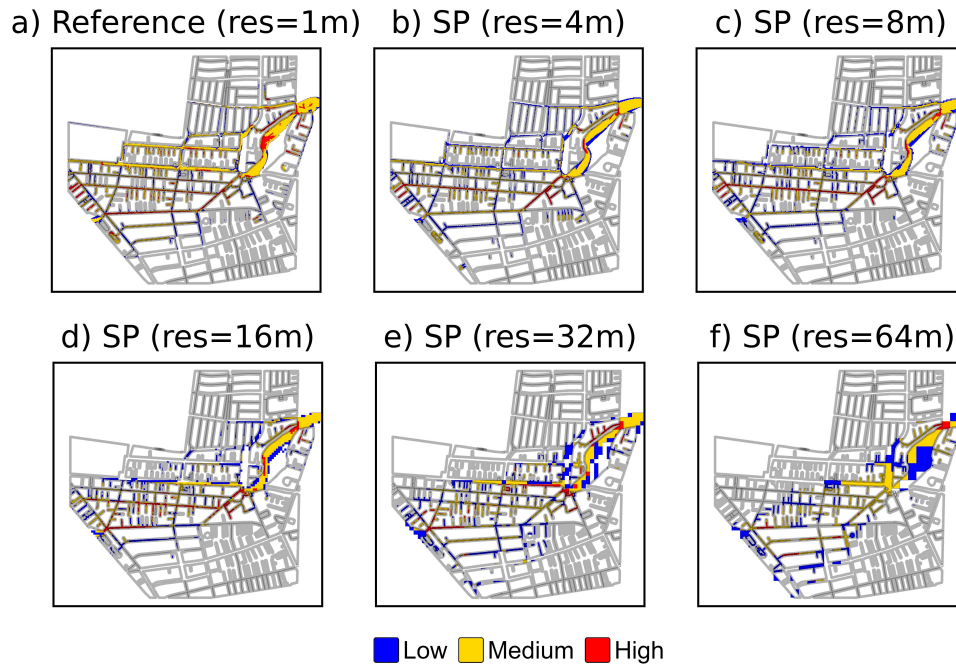


Figure 9: Hazard regions for case 2 according to the classification by Garcia and Lopez (2005). The systematic coarsening shows significant differences on the classification as the grid size is increased.

## 489 5. Conclusions

490 In this investigation we evaluate and quantify the ability of the SP model  
 491 to predict the water depths, flooded area, and the hazard index using differ-  
 492 ent spatial resolutions. The analysis is critical on the definition of the spatial  
 493 scale required to develop reliable FRA and fast response early-warning sys-  
 494 tems.

495 The results yield important insights on the adequate resolutions required  
 496 for the use of the PNSWE over NSWWE considering the large reduction in com-  
 497 putational time, analyzing the reproduced spatial distributions, and having

498 a quantification of the errors induced by mesh coarsening.

499 Here we developed a SP model computational implementation in a Carte-  
500 sian frame, introducing the building topography information at a sub-grid  
501 scale to reduce the computational time. To test the model with the most  
502 severe flooding conditions, we simulated dam-break flows for an idealized  
503 non-periodic city and a real-world urban zone in La Reina district using dif-  
504 ferent spatial resolutions. With the outputs of water depth and velocity, we  
505 assessed the ability to capture the maximum water depth, flood extension,  
506 and the hazard index according to the definition of Garcia and Lopez (2005).  
507 We compared the SP results with a fine-scale reference model in order to  
508 estimate the error of the sub-grid scale parameterization.

509 In general, the SP model captures all the main features of the flow when  
510 the resolution is equal to or below the street characteristic width  $SW$ . This  
511 is observed in both the idealized and real-world case. Moreover, when the  
512 resolution is very close to  $SW$ , the reduction in computation time is con-  
513 siderable, taking about 5% of the classical model CPU time while the main  
514 features of the flow are captured. Thus, the model has been found to be  
515 of great value when used at the meso-scale for these resolutions. The time  
516 reductions highlight the significant potential of the SP model for real-time  
517 forecasting and to implement early-warning systems.

518 When using SP, however, we found a diffusive-like behavior, especially  
519 when increasing significantly the mesh resolution. This effect is mainly due  
520 to the fact that by coarsening the mesh, the resolution of obstacles through  
521 the porosity term is gradually lost, and the flow has fewer impediments to  
522 spread throughout the floodplain. As a consequence, the maximum water

523 depth within the streets is generally underestimated by SP. Even though the  
524 diffusive-like behavior suggests that the flooded area will always be larger  
525 with SP, this result was not observed in the case 2 of La Reina district. The  
526 SP simulations obtained for this case showed a total area that is underesti-  
527 mated, as the grid cannot resolve details of the terrain that control the flood  
528 propagation. The area is underestimated since preferential flowpaths that  
529 are characteristic of the real urban area are not captured for coarse resolu-  
530 tions, many areas are not flooded for coarser meshes, and thus they present  
531 no hazard.

532 Results show that even though variables such as velocity may lose physical  
533 meaning when using a coarse mesh, composed variables for hazard assessment  
534 can maintain the main categories of the flood for resolutions below SW.

535 It is important to note that there is a tendency for SPOR to follow the  
536 bottom slope as the resolution increases too much compared with SW (like  
537 the 64m mesh for La Reina). This is explained because the porosity tends to  
538 be more homogeneous and the gradient is not able to capture the preferential  
539 flowpaths.

540 Finally, we obtained the smallest error in the idealized case compared to  
541 the real-world case, even at the same spatial resolution. This suggests that  
542 the error is directly affected by the complexity of the urban patterns and  
543 that it can potentially enhance the underestimation of some variables, like  
544 flow depth.

545 This emphasizes the need for testing these type of sub-grid models in real-  
546 world urban environments, where the meso-scale can deliver fairly accurate  
547 results with a much faster computation time than classical models, carefully

548 maintaining the street width when appropriate. These understanding can  
549 help to develop fast-response models approaching real-time forecasting for  
550 proper flood management and efficient decision-making.

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