Dear Dr. Xing Yuan

We are grateful for the constructive comments from the anonymous referee #3, and for your encouragement to revise this manuscript to be considered for publication in Hydrology and Earth System Sciences. We believe that this paper makes important novel contributions to the modeling of dynamic exposure to floods in city-regions and is of interest to the hydrological community. All comments from the anonymous referee #3 are fully addressed point by point as listed below, and all of the changes are tracked in the main manuscript. The tracked manuscript is attached at the end of this document.

If any further information is needed, please don't hesitate to contact us.
Yours Sincerely

Dr. Qiang Dai

Water and Environmental Management Research Centre

Department of Civil Engineering

University of Bristol, Bristol, BS8 1US, UK

Email: q.dai@bristol.ac.uk, qd_gis@163.com

Reply to Referee #3

Comments:

Point 1: The introduction of the other flood models in methodology between line 131-134 could either be removed or moved to introduction.

Reply: Agreed and the corresponding text has been moved to the Introduction section.

Point 2: Please check the format of the variables in the manuscript. All the variables should be in Italic.

Reply: Agreed and amended. The corresponding text (variables n, d, r, and t in line 162, 165, 175, and 177) has been revised in the manuscript.

Point 3: 3.2 ABM seems more like an introduction other than methodology, since it is still not clear how to apply ABM after reading this section. Suggest to rewrite this part.

Reply: To make it clear, we moved the contents of the Section 3.2 to the Section 1 and the previous Section 3.3. The details of how to apply ABM in our study was described in the previous Section 3.3 and 3.4. The following texts have been moved to Section 1 and the previous Section 3.3, respectively:

"Some modelling techniques, often collectively referred to as social simulation, have been successfully used to represent the behaviors of humans and organizations. These include event and fault trees, Bayesian networks, microsimulation, cellular automata, system dynamics, and agent-based models (ABMs). Research methods based on ABMs have been gradually introduced to the field of natural disaster risk assessment as these can simulate population distribution as well as interactions among the population (as the disaster victims), hazard factors, and disaster-prone environments (Yin, et al., 2016b)."

"An ABM is a computational method for simulating the actions and interactions of autonomous decision-making entities in a network or system to subsequently assess their effects on the system as a whole. Individuals and organizations represent agents, each of which individually assesses its situation and makes decisions based on a set of rules. Agents may execute various behaviors appropriate for the system component they represent (such as producing or consuming). Therefore, an ABM consists of a system of agents and the relationships between them. Even a simple ABM can exhibit complex behavior patterns because a series of simple interactions between individuals may result in more complex system-scale outcomes that could not have been predicted just by aggregating individual agent behaviors."

Point 4: 3.4 did you get the probability through the survey? How the probability is derived should be clarified. The content of questionnaire is strongly suggested to be added as supplementary material.

Reply: We calculated the probability based on the activity patterns derived from the survey data. The questionnaire has been attached as supplementary material with the manuscript. The probability of residents' activity patterns was estimated by (1) classifying residents according to their social characteristics, (2) summarizing their daily activity patterns and estimating the probability of each activity, and (3) using their reported flood risk perception to calculate expected changes in activity patterns during disaster scenarios and estimate the probability of different responses being taken by different types of residents. The following texts have been added in the manuscript:

"Travel survey data from a questionnaire (see Supplementary Material) were used to generate daily routines."

"To capture the variability in the travel survey and the uncertainties in behavior, synthetic daily routines were described in probabilistic terms based on the activity patterns derived from survey data. The probability of residents' activity patterns was estimated by (1) classifying residents according to their social characteristics, (2) summarizing their daily activity patterns and estimating the probability of each activity, and (3) using their reported flood risk perception to calculate expected changes in

activity patterns during disaster scenarios and estimate the probability of different responses being taken by different types of residents."

Point 5: In the discussion and conclusion part, the authors made a statement of what the research has done (line 474-481), the feature of the study (482-491), the limitation of the research (line 492-516). But there is a lack of the summary of the result, what could we learn from the results based on this study, what is the contribution of the study to the current development of the field and the comparison to other studies. It is suggested that this section could be divided into discussion and conclusion, which could give a fuller insight of the research.

Reply: Agreed and the following text has been added in Section 5:

"The high-resolution dynamic exposure of population, roads, and buildings to flooding estimated using the proposed method can play a significant role in assessing hazard risk and loss, thus supporting government efforts toward disaster risk management. As flood exposure constantly changes over short periods of time, such simulations allow the government to reasonably formulate emergency plans to minimize casualties and property losses while providing effective reference information for residents.

This study had four major findings. First, water depth was the major factor affecting total urban exposure to flooding in Lishui. Second, the population distribution on weekends was more variable than that on weekdays and was more sensitive to floods. Third, urban areas exposed to fluvial floods were concentrated along the river, while those to pluvial floods were relatively dispersed and independent. Roads had more blocks exposed to fluvial floods (8%) than pluvial floods (6%). Fourth, staying home was not the best individual choice, so residents' response behavior based on their subjective consciousness may result in increased overall exposure. This suggests that simple governmental alerts relating to the occurrence of urban flooding are insufficient for reducing urban exposure to flood hazards."

1　**Modelling the high-resolution dynamic exposure to flood in city-region**

2　Xuehong Zhu[1], Qiang Dai[1, 2, *], Dawei Han[2], Lu Zhuo[2], Shaonan Zhu[3], Shuliang Zhang[1, *]

3　[1]Key Laboratory of VGE of Ministry of Education, Nanjing Normal University, Nanjing, China

4　[2]WEMRC, Department of Civil Engineering, University of Bristol, Bristol, UK

5　[3]College of Geographical and Biological Information, Nanjing University of Posts and

6　Telecommunications, Nanjing, China

7　*Correspondence: q.dai@bristol.ac.uk

8　**Abstract:**

9　Urban flooding exposure is generally investigated with the assumption of stationary disasters and

10　disaster-hit bodies during an event, and thus cannot satisfy the increasingly elaborate modelling

11　and management of urban floods. In this study, a comprehensive method was proposed to simulate

12　dynamic exposure to urban flooding considering residents' travel behavior. First, a flood

13　simulation was conducted using the LISFLOOD-FP model to predict the spatio-temporal

14　distribution of flooding. Second, an agent-based model was used to simulate residents' movements

15　during the urban flooding period. Finally, to study the evolution and patterns of urban flooding

16　exposure, the exposure of population, roads, and buildings to urban flooding was simulated using

17　Lishui, China as a case study. The results showed that water depth was the major factor affecting

18　total urban exposure in Lishui. Urban exposure to fluvial flooding was concentrated along the river,

19　while exposure to pluvial flooding was dispersed throughout the area (independent from the river).

20　Additionally, the population distribution on weekends was more variable than on weekdays and

21　was more sensitive to floods. In addition, residents' response behavior (based on their subjective

22　consciousness) may result in increased overall exposure.~~The results showed that urban flooding~~

23　~~and population distribution had evident spatio-temporal variations. Additionally, the exposure~~

24　~~increased with increasing rainfall intensity and flooding extent. The urban area near the Oujiang~~

25　~~River was the most severely flooded, resulting in the highest exposure of population, roads, and~~

26   ~~buildings. Furthermore, the impacts of flooding on roads were greater than those on the population~~

27   ~~and on buildings.~~ This study presents the first fully formulated method for dynamic urban flood

28   exposure simulation at a high spatio-temporal resolution. The quantitative results of this study can

29   provide fundamental information for urban flood disaster vulnerability assessment, socioeconomic

30   loss assessment, urban disaster risk management, and emergency response plan establishment.

31   **Keywords:** urban flooding; resident travel behavior; agent-based model; dynamic exposure

32   **1.   Introduction**

33   Storm flooding has become increasingly frequent and severe with the intensification of global

34   warming and the rising frequency of extreme weather events (*Dankers and Feyen, 2008*;

35   *Hammond et al., 2015*). Urban floods have become major natural disasters in many cities around

36   the world and have created serious threats to human life and social and economic activities (*Gain*

37   *et al., 2015*). Effectively coping with floods and their adverse effects is an important part of disaster

38   prevention and mitigation as well as disaster risk management (*Atta-Ur-Rahman, 2014*). Non-

39   engineering measures such as exposure assessment are currently the main way of managing urban

40   flooding risk (*Chen et al., 2015*). Exposure refers to the presence of people, livelihoods,

41   environmental services and resources, infrastructure, or economic, social, or cultural assets in

42   places that could be adversely affected by natural disasters (*IPCC, 2012*). Urban flood disasters

43   are caused by the adverse effects of heavy rain and other factors on the city system in certain

44   disaster-prone environments. These events consist of three parts: disaster-causing factors, disaster-

45   prone environments, and disaster-hit bodies (*Shi, 1996*).

46   The characteristics of flood disasters and building environments and the distribution of population

47   and socio-economic resources are the key factors for evaluating urban flood exposure due to the

48   dynamic evolution of urban floods and disaster-hit bodies. The methods used for evaluating

49   exposure to urban flooding at a certain time or period vary due to changes in the disaster-hit bodies,

50   study areas, and data acquisition methods (*Röthlisberger et al., 2017*). Index-based methods are

51   commonly used for comprehensive exposure evaluation (*Mahe et al., 2005*; *Mansur et al., 2016*;

52   *Guo et al., 2014*). Statistical methods based on historical disaster data are also utilized (*Moel et al.,*

53   *2011*).

54   With respect to spatial considerations, the currently implemented method for estimation of disaster

55   exposure adopts the administrative boundaries of socioeconomic data, which are organized as

56   research units (*Yin, 2009*). Consequently, natural elements that have higher spatial resolutions must

57   be compromised due to the lower spatial resolution of human elements like population (*Yang et*

58   *al., 2013*). Therefore, a comprehensive and sophisticated geographic research unit has not been

59   established, thus resulting in simulation results applicable only to macro-scale planning and

60   decision making. Hence, the estimation of disaster exposure needs to incorporate greater spatial

61   heterogeneity and resolution.

62   Besides enhancement of the spatial scale, dynamic temporal simulation of disaster exposure has

63   gained increasing attention. Specifically, the dynamic evolution of disaster exposure at the macro

64   time scale considers exposure distribution as well as its variation during different development

65   periods (*Weis et al., 2016*). Therefore, this method is relatively mature and has led to abundant

66   research results. At the micro time scale, disaster-causing factors and disaster-hit bodies

67   represented by populations are constantly varying. On one hand, spatio-temporal changes in

68   disaster-causing factors (rainfall) result in corresponding dynamic changes in the characteristics

69   (water depth and velocity) of urban flood disasters. On the other hand, daily travel activities of

70   urban residents, such as commuting between residential and work or study areas, cause a dynamic

71 spatio-temporal distribution of the population. At the same time, the exposure to urban flooding

72 changes dramatically over a short period of time. To avoid or reduce disaster risks, casualties, and

73 property losses, different individuals are likely to adopt different adaptive behaviors, such as

74 delaying or cancelling travel plans, while the government is likely to adopt organizational actions

75 such as issuing warnings and evacuating residents (*Wan and Wang, 2017*; *Parker et al., 1995*).

76 Thus, the dynamic simulation of exposure requires the dynamic space-time simulation of

77 variations in the disaster, and disaster-hit bodies, as well as interactions between them.

78 Modelling of the spatio-temporal changes in natural disasters mainly uses the disaster system

79 simulation method, ~~such as the hydrological or hydrodynamic models used to simulate flood~~

80 ~~disasters~~ (*Werren et al., 2016*). A wide variety of existing hydrological or hydrodynamic models

81 capable of simulating fluvial or pluvial flooding are available~~; these~~, including~~e~~ the Storm Water

82 Management Model (SWMM) (*Rossman, 2015*), LISFLOOD (*Bates and De Roo, 2000*), MIKE-

83 SHE (*DHI, 2000*), MIKE-11 (*Havnø et al., 1995*), MOUSE (*Lindberg et al., 1989*), HEC-RAS

84 (*Brunner, 2008*), and HEC-HMS (*Charley et al., 1995*). ~~The c~~Change simulation~~s~~ of the disaster-

85 hit body (population) can use methods based on individual spatio~~ce~~ ~~time~~temporal data (*Liang et*

86 *al., 2015*) ~~and the agent-based method (Kang et al., 2012)~~. Although ~~the former~~this can acquire

87 human positions and movement tracks, it is difficult to identify the purpose of human activities,

88 ~~and~~ such that human disaster response behavior cannot be accurately simulated.

89 Some modelling techniques, often collectively referred to as social simulation, have been

90 successfully used to represent the behaviors of humans and organizations. These include event and

91 fault trees, Bayesian networks, microsimulation, cellular automata, system dynamics, and agent-

92 based models (ABMs). Research methods based on ABMs have been gradually introduced to the

93 field of natural disaster risk assessment as these ~~The agent-based model (ABM)~~ can ~~not only~~

94 simulate ~~the~~ population distribution ~~but can also~~as well as ~~simulate the~~ interactions among the

95 population (as the disaster victims), ~~the~~ hazard factors, and ~~the~~ disaster-prone environments (*Yin,*

96 *et al., 2016b*). Current research has used the ABM to simulate human responses to disasters, which,

97 in turn, have been used in natural disaster risk research (*Johnstone, 2012*; *Huang et al., 2015*).

98 Nevertheless, the simulation results do not reflect the exposure characteristics of the disaster-hit

99 bodies and their dynamic changes (*Dawson et al., 2011*).

100 Therefore, the objectives of this study were to develop a novel method using the LISFLOOD-FP

101 model (Sect. 3.1) and an ABM (Sect. 3.2) to simulate the exposure of urban populations, roads,

102 and buildings to flooding under varying conditions and subsequently implement the method as a

103 pilot in a real city. Several scenarios, including diverse flooding types and various responses of

104 residents to flooding, were considered in this regard. Additionally, dynamic features of the real

105 world were incorporated to improve the micro exposure analysis. This method was subsequently

106 applied to an urban area as a case study. Exposure simulation is a useful tool for estimating disaster

107 vulnerability and assessing losses, and the quantitative results under different scenarios of this

108 study are likely to benefit relevant government agencies in assessing risk, issuing warnings, and

109 planning emergency responses to urban natural disasters. In particular, considering the dynamic

110 distribution of the population under flooding, a more reasonable mitigation measure can be taken

111 to minimize casualties.

112 **2. Study area and data source**

113 In this study, Lishui City in Zhejiang Province, China, was considered as the study region because

114 of the availability of the required data and flooding history. The urban district of Lishui is a largely

115 hilly and mountainous area, and the Oujiang River traverses its southern and eastern parts. The

116   study area is located in the central district of Lishui, covers an area of 43.4 km^2, and has a large

117   population of about 71673 (Fig. 1). The frequencies of heavy rainstorms and persistent

118   concentrated rainfall events rise sharply in May and June during the Meiyu flood period, which

119   often results in flood disasters. On August 20, 2014, a heavy rainfall event lasting a few days

120   produced a 50-year flood in Lishui and caused considerable loss of property.

121   The datasets used in this study included a digital elevation model, rivers, roads, buildings,

122   population, and observation data consisting of river discharge and water level. Travel survey data

123   from a questionnaire (see Supplementary Material) were used to generate daily routines.

124   Additionally, traffic flow and water accumulation data were used for validation. Table 1 describes

125   the sources and uses of the datasets.

126   The travel survey data used in this study were taken from a face-to-face questionnaire survey

127   conducted from July 8, 2018 to July 14, 2018. A total of 25 subdistricts were selected based on

128   sample selection. According to the distribution of the subdistricts, the investigators were divided

129   into five groups of at least four investigators per group. In each group, a senior researcher

130   monitored the survey process, coordinated questionnaire collection and checked the completeness

131   and validity of the questionnaires collected. Before each interview, the investigators explained the

132   purpose of the investigation and confidentiality principles. The respondents in the study

133   participated voluntarily, and were allotted enough time to answer the questionnaire. In total, 623

134   questionnaires were distributed, 589 were collected, and 500 valid responses were selected after

135   excluding incomplete questionnaires (the response rate was 80.3%). The distribution of the social

136   characteristics of the respondents coincided with the actual population distribution in the study

137   area.

3. Methodology

This study comprised three aspects: disaster simulation, human activity simulation, and dynamic exposure assessment (Fig. 2). The first step included fluvial and pluvial flooding simulation based on the LISFLOOD-FP model. The simulation of human activity utilized ABM to obtain the spatio-temporal distribution of the population under different scenarios. Finally, the developed model was combined with the results of the previous two steps to assess the dynamic exposure of the population, roads, and buildings to urban flooding.

3.1 Flood models

~~A wide variety of existing hydrological or hydrodynamic models capable of simulating fluvial or pluvial flooding are available; these include the Storm Water Management Model (SWMM) (*Rossman, 2015*), LISFLOOD (*Bates and De Roo, 2000*), MIKE-SHE (*DHI, 2000*), MIKE-11 (*Havnø et al., 1995*), MOUSE (*Lindberg et al., 1989*), HEC-RAS (*Brunner, 2008*), and HEC-HMS (*Charley et al., 1995*).~~ LISFLOOD-FP (*Bates et al., 2013*) is a coupled 1D/2D hydraulic model based on a raster grid and was designed for research purposes at the University of Bristol. LISFLOOD-FP uses a square grid as the computational grid to simulate one-dimensional river hydraulic changes and two-dimensional floodplain hydraulic changes. The applicability of the model has been verified by several studies (*Horritt and Bates, 2002*; *Bates and De Roo, 2000*). Therefore, the LISFLOOD-FP model was chosen for the simulation of fluvial and pluvial flooding.

Floodplain flows were described in terms of the continuity and momentum equations discretized over a grid of square cells, which allowed the model to represent 2D dynamic flow fields for the floodplain. It assumed that the flow between two cells was simply a function of the free surface height difference between those cells:

160 $$\frac{dh^{i,j}}{dt} = \frac{Q_x^{i-1,j} - Q_x^{i,j} + Q_y^{i,j-1} - Q_y^{i,j}}{\Delta x \Delta y},$$ (1)

161 $$Q_x^{i,j} = \frac{h_{flow}^{5/3}}{n} \left(\frac{h^{i-1,j} - h^{i,j}}{\Delta x}\right)^{1/2} \Delta y,$$ (2)

162 where $h^{i,j}$ is the free surface height of water at node (i,j), Δx and Δy are the cell dimensions, nn

163 is the effective grid scale Manning's friction coefficient for the floodplain, and Q_x and Q_y describe

164 the volumetric flow rates between the floodplain cells in the x and y directions, respectively. The

165 flow depth, h_{flow}, represents the depth through which water can flow between two cells, and dd

166 is defined as the difference between the highest free surface height of water in the two cells and

167 the highest bed elevation.

168 The types of flooding simulated in this study included pluvial and fluvial floods. The input of the

169 model included DEM, rainfall, channel, and floodplain friction data. When it comes to fluvial

170 flooding simulations, boundary conditions, including river, water level, and river discharge were

171 also needed. The output data were water depth and water velocity in the x and y directions,

172 respectively. Due to the lack of hourly rainfall observation data, we used designed rainfall data for

173 pluvial flood simulation. Synthetic rainfall data for a return period of 50 years were simulated

174 using the Chicago hyetograph method (CHM) (*Cen et al., 1998*). The rainfall data were determined

175 using the rainstorm intensity formula (Eq. (3)), rainfall duration time (T), and peak position (rr).

176 $$i = \frac{A(1 + c \log P)}{167(t+b)^n},$$ (3)

177 where i is the rainfall intensity (mm/min), P is the return period, and tt is the time. A, b, c and n

178 are parameters related to the characteristics of the local rainstorm and need solutions. A is the

179 rainfall parameter, i.e. the design rainfall (mm) for 1 min at a 10 year return period, c is the rainfall

180   variation parameter (dimensionless), and b is the rainfall duration correction parameter, i.e. the

181   time constant (min) that can be added to convert the curve into a straight line after logarithmic

182   calculation of the two sides of the rainstorm intensity formula. n is the rainstorm attenuation index,

183   which is related to the return period. The "r" refers to the relative rainfall peak time, i.e., the value

184   from zero to one. Zero means the maximum rainfall at the beginning of rainfall and one means the

185   maximum rainfall at the end of rainfall. To simulate the flood in 2014, we fixed r at 0.2 based on

186   the assumption that the peak is located at the one fifth point of the design hyetograph. Additionally,

187   the rainfall duration was 6 hours (6 am to 12 pm), and the accumulated rainfall was 148.59 mm.

188   The parameters A, b, c and n were estimated from the rainstorm intensity formula for Lishui City

189   obtained from the "Zhejiang City Rainstorm Intensity Formula Table" published by the Hangzhou

190   Municipal Planning Bureau (Table 2). The rainfall simulation results are shown in Fig. 3(a). The

191   river discharge and water level input data for fluvial flood simulation utilized observational data

192   from Lishui's 50-year flood in 2014, provided by the Liandu Hydrological Station (Fig. 3(b)). The

193   flow data for the Daxi and Haoxi Rivers on August 20, 2014 were obtained from the Xiaobaiyan

194   and Huangdu stations, respectively, and the observational data for water levels at the outlets were

195   those for the Kaitan Dam.

196   **3.2 ABM**

197   Several modelling techniques, often collectively referred to as social simulation, have been

198   successfully used to represent the behaviors of humans and organizations. These include event and

199   fault trees, Bayesian networks, microsimulation, cellular automata, system dynamics, and ABMs.

200   Research methods based on ABMs have been gradually introduced to the field of natural disaster

201   risk assessment. ABM is considered most suitable to address challenges associated with simulating

9

202 the complexity and dynamic variability of population exposure to flooding due to its capacity to

203 capture interactions and dynamic responses in a spatial environment (*Dawson et al., 2011*).

204 An ABM is a computational method for simulating the actions and interactions of autonomous

205 decision-making entities in a network or system to subsequently assess their effects on the system

206 as a whole. Individuals and organizations represent agents. Each agent individually assesses its

207 situation and makes decisions based on a set of rules. Agents may execute various behaviors

208 appropriate for the system component they represent — for example, producing or consuming.

209 Therefore, an ABM consists of a system of agents and the relationships between them. Even a

210 simple ABM can exhibit complex behavior patterns because a series of simple interactions

211 between individuals may result in more complex system-scale outcomes that could not have been

212 predicted just by aggregating individual agent behaviors.

213 The ABM was developed as a concept in the late 1940s, and substantial applications were realized

214 with the emergence of high-powered computing. Such applications include those in the political

215 sciences (*Axelrod, 1997*), management and organizational effectiveness, and the behavior of social

216 networks (*Sallach and Macal, 2001*; *Gilbert and Troitzsch, 2005*). In recent years, it has been

217 introduced to the geosciences and other fields to provide novel ideas for the study of modern

218 geography, including land use simulation and planning as well as residential choice and residential

219 space differentiation (*Benenson et al., 2002*). The urban flood disaster system is a typical complex

220 "natural and social" system. The introduction of ABM to simulate space-time distributions of

221 populations is expected to quantify the dynamic exposure of populations to urban flood disasters.

222 For example, *Dawson et al. (2011)* proposed a dynamic ABM for flood event management to

223 evaluate population vulnerability under different storm surge conditions, dam break scenarios,

224 flood warning times, and evacuation strategies.

225 ## 3.2 Spatio-temporal simulation of population distribution

226 An ABM is a computational method for simulating the actions and interactions of autonomous

227 decision-making entities in a network or system to subsequently assess their effects on the system

228 as a whole. Individuals and organizations represent agents, each of which individually assesses its

229 situation and makes decisions based on a set of rules. Agents may execute various behaviors

230 appropriate for the system component they represent (such as producing or consuming). Therefore,

231 an ABM consists of a system of agents and the relationships between them. Even a simple ABM

232 can exhibit complex behavior patterns because a series of simple interactions between individuals

233 may result in more complex system-scale outcomes that could not have been predicted just by

234 aggregating individual agent behaviors.

235 The ABM of residents' travels established in this study included two core elements (agents and

236 activities) and two basic elements (blocks and networks). Individual movements were simulated

237 by defining the activity patterns of different types of residents, allowing us to obtain the

238 distribution of the population at each moment.

239 Residents were independent individuals with subjectivity, abstracted as agents in this study. Only

240 a limited number of agent classifications were used to reduce the number of agent types. The types

241 of agents were classified according to the social characteristics of the residents. Age and gender

242 characteristics mainly affect the ability of people to respond to disasters. The self-help abilities of

243 minors under 18 years of age and residents older than 60 years are generally poor. In the event of

244 natural disasters, they are generally categorized as the objects of help. The middle-aged group (18–

245 60 years old) generally has greater physical strength with a better ability to cope with disasters.

246 Unemployed people are more vulnerable to natural disasters. On one hand, their living

247   environments and resistance to disasters are poor; on the other hand, their economic conditions are

248   limited, which impedes recovery after the disaster and seriously affects their daily life in the short

249   term. Education level is related to the possibility of receiving early warning information by the

250   individual. Individuals with higher education levels are more likely to respond to early warning

251   information and are more aware of disasters than others (*Terti et al., 2015*; *Shabou et al., 2017*).

252   Additionally, different travel modes have different effects on the activity patterns of people as well

253   as on exposure levels when disasters occur. Therefore, the agent types were divided according to

254   age, gender, employment status, education level, and travel mode.

255   Activities were classified as work, study, recreation, shopping, at-home, and travel. An activity

256   pattern consisted of a series of activities to describe the spatio-temporal distribution of the agent.

257   The location and scope of an agent were restricted to blocks and networks. Different types of

258   agents indicated different activity patterns, and the same agent type could also indicate different

259   activity patterns in different scenarios. The travel survey data were used according to the

260   demographic properties of the agent to generate synthetic daily routines. To capture the variability

261   in the travel survey and the uncertainties in behavior, synthetic daily routines were described in

262   probabilistic terms based on the activity patterns derived from survey data. The probability of

263   residents' activity patterns was estimated by (1) classifying residents according to their social

264   characteristics, (2) summarizing their daily activity patterns and estimating the probability of each

265   activity, and (3) using their reported flood risk perception to calculate expected changes in activity

266   patterns during disaster scenarios and estimate the probability of different responses being taken

267   by different types of residents. Figure 4 presents an example of the synthetic daily routine of an

268   agent with the following demographic characteristics: male agent, aged 18–60 years, and

269   employed. In this example, the agent started the day at 8 am on a weekday. The agent then had a

270   0.8 probability of going straight to work, subsequently went home, and so on.

271   The study area was discretized into many blocks to improve the spatial resolution of the exposure

272   results. The major factors that affect the flood exposure are considered, including rivers, roads,

273   land use, and buildings. The discretization procedure was conducted with geographic information

274   system (GIS) tools (intersection and editing tools of the ArcGIS software) (*Lü et al., 2018*). Blocks,

275   the smallest unit of exposure, were defined as activity places locations for agents and represented

276   the smallest unit of exposure. This study were divided the block into five categories: residential

277   area, school, company, recreational area, and river. Additionally, the rResidential areas were

278   subdivided into classes I, II, III, and IV classes according to the type of building.

279   In this study, the network referred to roads and restricted the spatial travel scope of an intelligent

280   agent. Rural roads, highways, and urban roads (including main roads, sub trunk roads, and its

281   branches) were included in the network. The route selection criteria were defined once the different

282   activities from each individual's schedule were located, and road section attributes were specified.

283   Although various factors are involved in the route choice selection process, several studies have

284   indicated that minimizing travel time is the principal criterion for selecting routes (*Papinski et al.,*

285   *2009*; *Ramming, 2001*; *Bekhor et al., 2006*). Here, a simple but effective shortest path method was

286   used. The classical Dijkstra algorithm is a single-source shortest path algorithm that provides trees

287   of minimal total length and time in a connected set of nodes (*Dijkstra, 1959*). The activity pattern

288   attributions concerned only the starting times and durations of the activity sequences, thus

289   indicating that the travel duration for each individual was computed based on the distance between

290   the different activity locations. Therefore, the implemented schedules may be distorted compared

291   to the assigned schedules in terms of travel durations (*Terti et al., 2015*). We can get the departure

292 and destination block of each stage according to the activity patterns, and then calculate the shortest

293 path consisting of a series of road sections. At each moment, the block in which the agent is located

294 is calculated. If on the road, according to differences in the speed of walking, riding a bus, or

295 driving a car, the road section location is calculated. During flooding, this is similar in every aspect

296 except the activity patterns.

297 **3.3 Impacts of disasters on anthropogenic activities**

298 This study accounted for the adaptability or adjustment behavior of residents to disasters during

299 the disaster event. The type of activity and its sensitivity to disaster affected the residents' disaster

300 response behavior. Recreation and shopping activities were easier to cancel and postpone than

301 work and study (*Cools et al., 2010*). The sensitivities of residents to disasters depended on their

302 socioeconomic characteristics and risk factors such as disaster- (flood-) related knowledge and

303 experience. People with higher education levels are more knowledgeable about disasters and are

304 more likely to receive early warning information and take effective measures (*Terti et al., 2015*).

305 Additionally, it is easier for workers to ignore the risks of a disaster (*Ruin et al., 2007*; *Drobot et*

306 *al., 2007*). Therefore, this study accounted for the impacts of education level on the response

307 behavior of residents to disaster events.

308 The impacts of a disaster on population distribution were determined by defining different activity

309 patterns and their changing probabilities. Figure 5 shows activity patterns during different disaster

310 scenarios for employed adult men who had received higher education. The "bad weather" scenario

311 was similar to the "daily activity" pattern. For instance, the change in travel probability during

312 "bad weather" due to a rainstorm reflected the adaptive behavior of residents. The "warning"

313 scenario assumed that the government had issued early warning information at 8 a.m., that schools

314   had suspended classes on weekdays, and the resident responses were stronger than those to the

315   "bad weather" scenario, thereby resulting in a greater difference in activity patterns.

316   **3.4 Dynamic exposure assessment**

317   The dynamic exposure was calculated based on the simulations of spatio-temporal distributions of

318   the population and flooding. Therefore, the exposure at each moment was calculated according to

319   the population distribution and flood data at that time. Based on the data availability, this study

320   focused only on three types of disaster-hit bodies, i.e., population, roads, and buildings.

321   (i) Population

322   Population exposure generally refers to the population exposed to the impacts of disaster events

323   and is characterized by regional population size or density. This study selected the exposed

324   population and accounted for vulnerable groups and road users. Age was the primary factor

325   impacting vulnerability. Specifically, the young (people under the age of 18 years) and the elderly

326   (people over 60 years old) were the vulnerable groups.

327   (ii) Roads

328   As the basic skeleton of a city, roads are not only the media for daily travel of passengers and

329   freight transportation but also disaster-hit bodies (*Yin, et al., 2016a*), as they are vulnerable to flood

330   disasters. This study selected the number and lengths of exposed roads to reflect road exposure.

331   (iii) Buildings

332   Aggravation of urban flooding has made building flooding more common in urban areas, resulting

333   in loss of internal property and construction structure. Additionally, the dynamic state of building

334   exposure is related to the safety of both the building as well as the surrounding population. In this

335   study, the area of the exposed building and the depth of accumulated water in the building were

336   considered as the building exposure.

337   **3.5 Scenario design**

338   The daily behaviors of people are characterized by certain patterns with regard to daily, weekly,

339   monthly, and annual cycles. The rainstorm ("bad weather") and disaster response measures

340   adopted by the organization ("warning") are likely to affect people's daily behaviors. Therefore,

341   12 scenarios, representing different flooding types and human activities, were designed in this

342   study (Table 3). S1, S2, S7, and S8 were control groups that indicated human activity with no rain

343   and no warning, while the rest of the scenarios were experimental groups.

344   **3.6 Model implementation and parameter setting**

345   ~~As an important spatial data management and analysis technology,~~ GIS, an important spatial data

346   management and analysis technology, plays an important role in dynamic exposure analysis of

347   urban floods. In addition, the Python programming language is being increasingly adopted by

348   researchers due to its~~Because of the~~ simplicity, readability, and flexible usability ~~extensibility of~~

349   ~~the Python programming language, an increasing number of research institutes are adopting it for~~

350   ~~development~~. Therefore, the model was developed using the Visual Studio Code software (*Visual*

351   *studio code, 2018*) and Python programming language (*Python, 2018*). The development of the

352   graphical user interface (GUI), GIS module, and drawing module ~~was realized by~~used Qt (*Qt,*

353   *2018*), Geopandas (*Geopandas, 2018*), and Matplotlib (*Matplotlib, 2018*), respectively.

354   (i) Block generation

355 Blocks are irregular vector units whose size represents spatial resolution. Therefore, the spatial

356 resolution of the results is related to the study area and data. In this study, the study area was

357 divided into 237 blocks based on the method introduced in Sect. 3.3, with a minimum area of

358 2731.64 square meters. The block types and their spatial distributions are shown in Fig. 6 and Fig.

359 7, respectively. Most of the blocks in the study area were categorized as residential area, while

360 blocks of recreational areas were few and concentrated.

361 (ii) Parameter setting

362 To reduce the number of agent types, only a limited number of agent classes were used. The

363 distribution of population characteristics for Liandu District is shown in Table 4. The agents were

364 divided into 18 types for normal daily (non-disaster) scenarios (S1, S2, S7, and S8) and 24 types

365 for disaster scenarios (other scenarios except S1, S2, S7, and S8) based on the influence of

366 education level on the individual disaster response behavior (Fig. 8).

367 Since the census data did not identify individuals ~~according to~~by address~~es~~, ~~at the start of~~ each

368 simulation~~,~~ began by creating an agent population with the same distributions of age, gender,

369 employment, education level, and travel mode ~~was~~ that was randomly located within the residential

370 area ~~for the case study~~. The synthetic daily routines were described in probabilistic terms to capture

371 the variability present in the travel survey and other uncertainties in behavior. The probabilities of

372 ~~agents'~~ all daily activities for all agents were generated based on the travel survey. ~~We estimated~~

373 ~~the probabilities of all the activities of the population groups under investigation.~~

374 (iii) Exposure threshold

375 Although flood fatalities can occur through a number of mechanisms, such as physical trauma,

376 heart attack, or electrocution, drowning accounts for two-thirds of the fatalities (*Jonkman and*

377 *Kelman, 2005*). Previous research has established that the probability of death or serious injury as

378 a result of exposure to flooding (*Abt et al., 1989*; *Karvonen et al., 2000*; *Lind et al., 2004*; *Jonkman*

379 *and Penning‑Rowsell, 2008*) is dominated by (1) the depth of floodwater and (2) the velocity of

380 floodwater. Additionally, the rate of water level rise can also play an important role in this regard.

381 However, other factors, such as age, fitness level, height, and weight of the individual, are also

382 important for determining their vulnerability to disasters. A comprehensive review of the flood-

383 related casualty data and methods used to assess the risk of death or serious harm to people caused

384 by flooding is was provided by the *Department for Environment Food and Rural Affairs and*

385 *Environment Agency (2003)* and *Jonkman and Penning‑Rowsell (2008)*. In this study, rather than

386 predicting mortality (which is subject to random factors as well as those mentioned previously),

387 exposure to floodwater depths of 25 cm or greater under relatively fast flowing (2.5 m/s or greater)

388 conditions was established as the threshold for the most vulnerable people (*DEFRA and*

389 *Environment Agency, 2003*). This provided a conservative estimate of individuals vulnerable to

390 floodwater rather than an estimate of mortality (*Dawson et al., 2011*).

391 Since building steps (thresholds) exert a blocking effect on shallow flooding, they are likely to

392 reduce the degree of flooding by restricting the flood water to the outside of the building, thereby

393 reducing the exposure of the building. Therefore, this study assigned building step height to

394 corresponding block types according to the architectural design standards of China and the actual

395 conditions of the study area (Table 5). Therefore, the exposure of the building was determined

396 according to the depth of the flood and the height of the building steps. The depth of the water

397 entering the building was the difference between the depth of the flood and the height of the steps.

398 **4. Results**

4.1 Flood simulation

The temporal resolution of flood simulation results was unified with other output results for half an hour. Figure 9 indicates the accumulated water depths and velocities of pluvial and fluvial floods in the study area. As is evident, the pluvial and fluvial floods exerted significant impacts, and the urban area near the Oujiang River was the most severely flooded. Additionally, water also accumulated in the inner areas of the city, mainly on roads, in case of pluvial flood disasters. The variations in water depth and velocity for seven severely flooded areas (including blocks and roads) are presented in Fig. 10. ~~As indicated, e~~Evident spatio-temporal variations in flooding were observed~~. Figures 9 and 10 indicate that~~ and water depth was the major factor affecting the total urban exposure to flooding in Lishui.~~water depth was the main factor causing life and property losses, whereas water velocity had little or no effect.~~

The flood simulation results were indirectly validated by actual water accumulation points. During the 50-year flood in 2014, the city had 10 flooded roads and 18 water accumulation points. The actual hydrological points selected according to the study area and the urban flooding results simulated by the prototype system are indicated in Fig. 11.

To avoid overlapping with the simulated water accumulation results for roads, the actual flooding points in the figure only included road junctions, and the entirety of Gucheng Road (Lutang Street to Dayou Street section) and Liyang Street (which connected the senior middle school to the Sanyan Temple section) was represented by corresponding intersection points. Figure 11 indicates that both the simulation results and the actual water accumulation points were mainly distributed along the river. The simulated water accumulation area (Fig. 11(a)) included roads in the center of the city and was larger than the actual flooding area. This difference could be attributed to different

421   definitions of "water accumulation". The simulation results presented in Figure 11 included all

422   areas where the accumulated water depth during the flooding period was greater than 15 cm. The

423   actual water accumulation point was defined as one experiencing rainfall greater than 50 mm over

424   a 24 hour period. Additionally, it was characterized by the water accumulation depth of the road

425   reaching 15 cm (the meteorological department issued a blue rainstorm warning at this level), the

426   water withdrawal time reaching one hour, and the water accumulation scope value being greater

427   than 50 m^2. Certain gaps existed between the observational data and the actual river discharge

428   since the observation station was far from the study area. Hence, the results indicated that the

429   simulated water accumulation area during the fluvial flood (Fig. 11 (b)) was smaller than that of

430   the actual situation.

4.2 Simulation of the spatio-temporal distribution of population

432   The spatial and temporal resolutions of the modelling results could be adapted to the study area.

433   The area of the minimum block was 2731.64 m^2. The temporal resolution of the results was half

434   an hour, which could be set to 10 minutes or even 1 minute according to the requirements.

435   Additionally, no accurate traffic model was used to simulate agents' movements on road for two

436   reasons: (1) to improve efficiency and (2) we did not pay attention to high temporal-resolution

437   human movements (such as one minute or one second), but only focused on the population

438   distribution for a period of time, so the temporal resolution requirement of human activities was

439   low.

440   The spatio-temporal population distribution was simulated based on six scenarios: (1) daily,

441   weekday (S1, S7); (2) daily, weekend (S2, S8); (3) bad weather, weekday (S3, S9); (4) bad weather,

442   weekend (S4, S10); (5) warning, weekday (S5, S11); (6) warning, weekend (S6, S12). Figure 12

443   indicates the population variation for blocks and roads for the six scenarios. Figure 12(a) indicates

444   that, among the three weekend scenarios, the population in the playground (Block 77) changed

445   more than the population in the company (Block 113). Figure 12(b) indicates that the population

446   on the roads was volatile, and the morning peak hour during the weekend was delayed by an hour

447   in comparison to that during the weekdays. The population distribution in the study area is shown

448   in Fig. 13. The population was unevenly distributed and concentrated in recreational and

449   residential areas over the weekend. However, the population distribution on weekdays was

450   relatively uniform. The population distribution on weekends was more variable than that on

451   weekdays and was more sensitive to floods. The concurrent population distribution for the six

452   scenarios changed significantly during the weekend, while the distribution for weekdays changed

453   little.

454   Figures 12 and 13 indicate that the population change patterns were different for different blocks

455   types. The daily routines of most people started from the residential area (home) in the morning,

456   followed by school or company blocks during weekdays and recreational areas during weekends,

457   and, finally, concluded with a return to the residential area at night. During the occurrence of

458   rainstorms or the reception of warning messages, different types of people reacted differently

459   (continuing, postponing, or cancelling the originally planned activities). Vulnerable people, such

460   as the elderly and children, and sensitive people, such as the homeless, were more likely to cancel

461   travel plans. Additionally, recreational activities were more likely to be cancelled than were study

462   and work activities.

463   The reliability of the simulation of the spatio-temporal population distribution was indirectly

464   verified by utilizing traffic flow data. Due to the lack of data for 2014, we used traffic flow data

465   from June 24 to July 7, 2017. The simulated total number of residents passing the four intersections

466 (such as the junction of the Liqing and Huayuan roads) and the actual measured traffic flow at the

467 intersections during the morning and evening peak hours on weekdays and weekends are shown

468 in Table 6 and Table 7~~.~~, where "Sim." means simulation results, ~~and~~ "Obs." means measured

469 values ~~which are~~ (multi-day average results)~~.~~, "LQ" is Liqing Road, "KF" is Kaifa Road, "HY" is

470 Huayuan Road, "ZJ" is Zijin Road, and "LT" is Lutang Street. The deviation ratio was calculated

471 as: (Sim. -- Obs.) / Obs.

472 In theory, the simulated value should be much larger than the measured value since the former

473 indicates the number of people while the latter represents the number of cars and buses. However,

474 as indicated in Table 6 and Table 7, the simulated value was close to the measured value. This

475 could be attributed to the assumption that the study area was closed and the simulated population

476 was the number of permanent residents, excluding the migrant population. In reality, the number

477 of migrants in the urban area during daytime is large owing to its geographical location. Moreover,

478 this study simplified human activities when simulating the spatio-temporal distribution of the

479 population. Therefore, the number of pedestrians on the road was small. However, there was a

480 deviation ratio of about ±5% between the simulated value and the measured value, except for three

481 deviation ratios of about ±10%. Therefore, the simulation method for the spatio-temporal

482 distribution of population is feasible, and the results are reliable.

483 **4.3 Dynamic exposure assessment**

484 Figure 14 presents the population exposure variation for two selected areas. The difference

485 between pluvial and fluvial flood scenarios could be attributed to differences in the changes and

486 degrees of water accumulation. Figure 14(a) indicates that population exposure was the highest for

487 the daily scenario, followed by the bad weather scenario and minimum warning scenario. However,

488   as indicated in Fig. 14(b), the population was most exposed to both weekend and weekday warning

489   scenarios. This is due to the assumption that the disaster response behavior adopted by residents

490   was to reduce travel, i.e., the refuge of residents was the residential area. Additionally, the response

491   was not based on the exposure of the residential area. Therefore, when residential areas, such as

492   Block 6, were exposed to floods, the residents chose to reduce travel, thus resulting in an increase

493   in the population of residential areas and consequently increasing the population exposure. Thus,

494   if the government informs the residents of Block 6 in advance about the location of appropriate

495   shelters, the exposed population will be effectively reduced. The method proposed in this study

496   can also help determine vulnerable populations and road users in the exposed blocks.

497   Figure 15 presents variations in the road and building exposures of two selected areas with serious

498   flooding. The road and building exposures for the study area are presented in Fig. 16. It can be

499   concluded that road and building exposures during pluvial and fluvial floods also varied with the

500   flood depth. The urban area exposed to fluvial floods was concentrated along the river, while that

501   exposed to pluvial floods was relatively dispersed and independent. Additionally, the exposed road

502   length of the block fluctuated, while the buildings were either entirely exposed or not exposed.

503   Furthermore, the area of the road affected by pluvial and fluvial floods was greater than that of the

504   buildings. As indicated in Fig. 16, exposed buildings were present only in a few areas (3 blocks

505   for pluvial flood and 4 blocks for fluvial flood), while roads were affected in several areas (19

506   blocks for pluvial flood and 15 blocks for fluvial flood). In addition, buildings were the least

507   exposed due to high thresholds or the number of building steps designed and built in recent years,

508   while roads and population were severely affected by floods.

509   **5. Discussion and conclusions**

510 Urban flooding considerably impacts the life of residents, in terms of both daily commuting and

511 casualties. This study proposed a method for obtaining high-resolution dynamic exposure to urban

512 flooding. First, the spatio-temporal distributions of pluvial and fluvial floods were simulated by

513 the LISFLOOD-FP model. Second, the responses of residents to bad weather and government

514 measures (warnings) were incorporated to develop an ABM to simulate residents' activities during

515 flooding. Finally, urban exposure during different flood scenarios was comprehensively simulated

516 and was based on the population and hydrological simulation results, road and building data, and

517 the case study of the Lishui urban district.

518 ~~The proposed method can provide the government with high resolution dynamic exposure of~~

519 ~~population, roads, and buildings to flooding along with information for urban vulnerability and~~

520 ~~loss assessment, thus supporting the government disaster risk management. Additionally, it could~~

521 ~~provide effective reference information for residents' travels. In summary, this study had four main~~

522 ~~elements. First, different spatio-temporal distributions of water depth and velocity predictions were~~

523 ~~obtained using the LISFLOOD-FP model. Second, an ABM was utilized to simulate the spatio-~~

524 ~~temporal distributions of the population. Third, the impacts of pluvial and fluvial floods on~~

525 ~~buildings were found to be small, while that on roads and the population was evident. Finally, if~~

526 ~~residents simply reduced their travels (stayed at home), the exposure of the population in the~~

527 ~~exposed residential areas increased.~~

528 The high-resolution dynamic exposure of population, roads, and buildings to flooding estimated

529 using the proposed method can play a significant role in assessing hazard risk and loss, thus

530 supporting government efforts toward disaster risk management. As flood exposure constantly

531 changes over short periods of time, such simulations allow the government to reasonably formulate

532   emergency plans to minimize casualties and property losses while providing effective reference

533   information for residents.

534   This study had four major findings. First, water depth was the major factor affecting total urban

535   exposure to flooding in Lishui. Second, the population distribution on weekends was more variable

536   than that on weekdays and was more sensitive to floods. Third, urban areas exposed to fluvial

537   floods were concentrated along the river, while those to pluvial floods were relatively dispersed

538   and independent. Roads had more blocks exposed to fluvial floods (8%) than pluvial floods (6%).

539   Fourth, staying home was not the best individual choice, so residents' response behavior based on

540   their subjective consciousness may result in increased overall exposure. This suggests that simple

541   governmental alerts relating to the occurrence of urban flooding are insufficient for reducing urban

542   exposure to flood hazards.

543   It should be noted that there is no comprehensive way to verify the proposed method because

544   parameters of human behavior and psychological processes are difficult (or, to some extent,

545   impossible) to obtain. In this study, the proposed method was verified indirectly. The actual traffic

546   information for each road intersection was collected and compared with the simulated population

547   results. Additionally, the information for actual water accumulation points was compared with the

548   simulated water accumulation results.

549   However, a few limitations persist. For instance, considerable uncertainties regarding the use and

550   design of the ABM exist. These include differences in the responses of residents of the same type

551   to disasters in the same scenario. Therefore, based on the survey data, we designed simplified

552   activity patterns, which are consistent with the actual situation of the study area. Moreover,

553   simplification of the behavior patterns and disaster responses of residents is inevitable, resulting

554   in differences between the simulation results and reality.

555   Based on the analysis of the indirect validation results, we also found several problems. Since the

556   migrant population and the exchange between the city and the outside were not considered, the

557   simulated road population was small, so we needed to use real-time traffic data (such as taxi

558   trajectories and card data from public transportation) to calibrate activity patterns to obtain more

559   realistic population distribution results. Moreover, the actual water accumulation point information

560   cannot be completely consistent with the simulation result because of its definition, therefore the

561   simulation result can only be roughly verified. We need more abundant and accurate historical

562   hazard data to fine-tune the flood simulation results. Our study focused more on the explorative

563   method, while the result is just an application case. Due to the limitation of the study area and data,

564   the current results are quite general in an early stage. The method proposed also has many areas in

565   need of improvements, such as the design of ABM. Therefore, future studies should focus on

566   optimizing the proposed method and practical case studies, which may produce more informative

567   results.

568   **Acknowledgements**

573   **References**

574 Abt, S. , Wittier, R. , Taylor, A. and Love, D.: HUMAN STABILITY IN A HIGH FLOOD
575   HAZARD ZONE1. JAWRA Journal of the American Water Resources Association, 25:
576   881-890, https://doi.org/10.1111/j.1752-1688.1989.tb05404.x, 1989.

577 Atta-Ur-Rahman, D.: Disaster risk management, 2014.

578 Axelrod, R.: The complexity of cooperation: Agent-based models of competition and
579   collaboration (Vol. 3). Princeton University Press, 1997.

580 Bates, P. D., and De Roo, A. P. J.: A simple raster-based model for flood inundation simulation.
581   Journal of hydrology, 236(1-2), 54-77, https://doi.org/10.1016/S0022-1694(00)00278-X,
582   2000.

583 Bates, P., Trigg, M., Neal, J., Dabrowa ,A.: LISFLOOD-FP User manual, Code release 5.9.6,
584   School of Geographical Sciences, University of Bristol, University Road, Bristol, BS8 1SS,
585   UK, 2013. Available online at University of https://www.bristol.ac.uk/media-
586   library/sites/geography/migrated/documents/lisflood-manual-v5.9.6.pdf.

587 Bekhor, S., Ben-Akiva, M. E., and Ramming, M. S.: Evaluation of choice set generation
588   algorithms for route choice models. Annals of Operations Research, 144(1), 235-247,
589   https://doi.org/10.1007/s10479-006-0009-8, 2006.

590 Benenson, I., Omer, I., and Hatna, E.: Entity-based modeling of urban residential dynamics: the
591   case of Yaffo, Tel Aviv. Environment and Planning B: Planning and Design, 29(4), 491-
592   512, https://doi.org/10.1068/b1287, 2002.

593 Brunner, G. W.: HEC-RAS River Analysis System User's Manual Version 4.0. US Army Corps
594   of Engineers, Hydrologic Engineering Center. Report CPD-68, 2008.

595 Cen, G., Shen, J., and Fan, R.: Research on rainfall pattern of urban design storm. Advances in
596   Water Science, 9(1), 41-46, https://doi.org/10.14042/j.cnki.32.1309.1998.01.007, 1998.

597 Charley, W., Pabst, A., Peters, J.: The Hydrologic Modeling System (HEC-HMS): Design and
598   Development Issues. Hydrological Engineering Center, US Army Corps of Engineers,
599   Technical Paper No. 149, 1995.

600 Chen, Y., Zhou, H., Zhang, H., Du, G., and Zhou, J.: Urban flood risk warning under rapid
601   urbanization. Environmental research, 139, 3-10,
602   https://doi.org/10.1016/j.envres.2015.02.028, 2015.

603 Cools, M., Moons, E., Creemers, L., and Wets, G.: Changes in travel behavior in response to
604   weather conditions: do type of weather and trip purpose matter?. Transportation Research
605   Record: Journal of the Transportation Research Board, (2157), 22-28,
606   https://doi.org/10.3141/2157-03, 2010.

607 Danish Hydraulic Institute (DHI).: MIKE SHE Water movement user manual. DHI Water &
608   Environment, 2000.

609 Dankers, R., and Feyen, L.: Climate change impact on flood hazard in Europe: An assessment
610   based on high‑resolution climate simulations. Journal of Geophysical Research:
611   Atmospheres, 113(D19), https://doi.org/10.1029/2007JD009719, 2008.

Dawson, R. J., Peppe, R., and Wang, M.: An agent-based model for risk-based flood incident management. Natural hazards, 59(1), 167-189, https://doi.org/10.1007/s11069-011-9745-4, 2011.

DEFRA and Environment Agency.: Flood risks to people phase 1: R&D Technical Report FD2317. DEFRA, London, 2003.

Dijkstra, E. W.: A note on two problems in connexion with graphs. Numerische mathematik, 1(1), 269-271, 1959.

Drobot, S. D., Benight, C., and Gruntfest, E. C.: Risk factors for driving into flooded roads. Environmental Hazards, 7(3), 227-234, https://doi.org/10.1016/j.envhaz.2007.07.003, 2007.

Gain, A. K., Mojtahed, V., Biscaro, C., Balbi, S., and Giupponi, C.: An integrated approach of flood risk assessment in the eastern part of Dhaka City. Natural Hazards, 79(3), 1499-1530, https://doi.org/10.1007/s11069-015-1911-7, 2015.

Geopandas: http://geopandas.org/, 2018.

~~Gilbert, N., and Troitzsch, K.: Simulation for the social scientist. McGraw-Hill Education (UK), 2005.~~

Guo, E., Zhang, J., Ren, X., Zhang, Q., and Sun, Z.: Integrated risk assessment of flood disaster based on improved set pair analysis and the variable fuzzy set theory in central Liaoning Province, China. Natural hazards, 74(2), 947-965, https://doi.org/10.1007/s11069-014-1238-9, 2014.

Hammond, M. J., Chen, A. S., Djordjević, S., Butler, D., and Mark, O.: Urban flood impact assessment: A state-of-the-art review. Urban Water Journal, 12(1), 14-29, https://doi.org/10.1080/1573062X.2013.857421, 2015.

Havnø, K., Madsen, M. N., and Dørge, J.: MIKE 11–a generalized river modelling package. Computer models of watershed hydrology, 733-782, 1995.

Horritt, M. S., and Bates, P. D.: Evaluation of 1D and 2D numerical models for predicting river flood inundation. Journal of hydrology, 268(1-4), 87-99, https://doi.org/10.1016/S0022-1694(02)00121-X, 2002.

Huang, H., Fan, Y., Yang, S., Li, W., Guo, X., Lai W., and Wang H.: A multi-agent based theoretical model for dynamic flood disaster risk assessment. Geographical Research, 34(10):1875-1886, https://doi.org/10, 1875-1886, 10.11821/dlyj20151006, 2015.

IPCC.: Summary for Policymakers. In: Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation. A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, UK, and New York, NY, USA, pp. 3-21, 2012.

Johnstone, M. A.: Life safety modelling framework and performance measures to assess community protection systems: application to tsunami emergency preparedness and dam safety management, Ph.D. thesis, University of British Columbia, 2012.

Jonkman, S. N., and Kelman, I.: An analysis of the causes and circumstances of flood disaster deaths. Disasters, 29(1), 75-97, https://doi.org/10.1111/j.0361-3666.2005.00275.x, 2005.

Jonkman, S. N., and Penning‑Rowsell, E.: Human Instability in Flood Flows 1. JAWRA Journal of the American Water Resources Association, 44(5), 1208-1218, https://doi.org/10.1111/j.1752-1688.2008.00217.x, 2008.

~~Kang, T., Zhang, X., Zhao, Y.,Wang, Y., and Zhang, W.: Agent-based Urban Population Distribution Model. Scientia Geographica Sinica, 32(7): 90-797, https://doi.org/10.13249/j.cnki.sgs.2012.07.003, 2012.~~

Karvonen, R. A., Hepojoki, A., Huhta, H. K., and Louhio, A.: The use of physical models in dam-break analysis. RESCDAM Final Report. Helsinki University of Technology, Helsinki, Finland, 2000.

Liang, Y., Wen, J., Du, S., Xu, H., and Yan J.: Spatial-temporal Distribution Modeling of Population and its Applications in Disaster and Risk Management. Journal of Catastrophology, 30(04):220-228, https://doi.org/ 10.3969/j.issn.1000-811X.2015.04.038, 2015.

Lind, N., Hartford, D., and Assaf, H.: Hydrodynamic models of human stability in a flood 1. JAWRA Journal of the American Water Resources Association, 40(1), 89-96, https://doi.org/10.1111/j.1752-1688.2004.tb01012.x, 2004.

Lindberg, S., Nielsen, J. B., and Carr, R.: An integrated PC-modelling system for hydraulic analysis of drainage systems. In Watercomp'89: The First Australasian Conference on Technical Computing in the Water Industry; Preprints of Papers (p. 127). Institution of Engineers, Australia, 1989.

Lü, G., Batty, M., Strobl, J., Lin, H., Zhu, A. X., and Chen, M.: Reflections and speculations on the progress in Geographic Information Systems (GIS): a geographic perspective. International Journal of Geographical Information Science, 1-22, https://doi.org/10.1080/13658816.2018.1533136, 2018.

Mahe, G., Paturel, J. E., Servat, E., Conway, D., and Dezetter, A.: The impact of land use change on soil water holding capacity and river flow modelling in the Nakambe River, Burkina-Faso. Journal of Hydrology, 300(1-4), 33-43, https://doi.org/10.1016/j.jhydrol.2004.04.028, 2005.

Mansur, A. V., Brondízio, E. S., Roy, S., Hetrick, S., Vogt, N. D., and Newton, A.: An assessment of urban vulnerability in the Amazon Delta and Estuary: a multi-criterion index of flood exposure, socio-economic conditions and infrastructure. Sustainability Science, 11(4), 625-643, https://doi.org/10.1007/s11625-016-0355-7, 2016.

Matplotlib: https://matplotlib.org/, 2018.

Moel, H. D., Aerts, J. C., and Koomen, E.: Development of flood exposure in the Netherlands during the 20th and 21st century. Global Environmental Change, 21(2), 620-627, https://doi.org/10.1016/j.gloenvcha.2010.12.005, 2011.

Nasiri, H., Mohd Yusof, M.J., and Mohammad Ali, T.A.: An overview to flood vulnerability assessment methods. Sustain. Water Resour. Manag., 2: 331, https://doi.org/10.1007/s40899-016-0051-x, 2016.Papinski, D., Scott, D. M., and Doherty, S. T.: Exploring the route choice decision-making process: A comparison of planned and

691   observed routes obtained using person-based GPS. Transportation research part F: traffic
692   psychology and behaviour, 12(4), 347-358, https://doi.org/10.1016/j.trf.2009.04.001, 2009.

693 Parker, D., Fordham, M., Tunstall, S., and Ketteridge, A. M.: Flood warning systems under stress
694   in the United Kingdom. Disaster Prevention and Management: An International Journal,
695   4(3), 32-42, https://doi.org/10.1108/09653569510088050, 1995.

696 Python: https://www.python.org/, 2018.

697 Qt: https://www.qt.io/, 2018.

698 Ramming, M. S.: Network knowledge and route choice, Unpublished Ph. D. Thesis,
699   Massachusetts Institute of Technology, 2001.

700 Rossman, L. A.: Storm water management model user's manual Version 5.1 EPA-600/R-
701   14/413b[z]. National Risk Management Laboratory Laboratory Office of Research and
702   Development U. S. Environmental Protection Agency, 2015. Available online at
703   https://nepis.epa.gov/Exe/ZyPDF.cgi/P100N3J6.PDF?Dockey=P100N3J6.PDF

704 Röthlisberger, V., Zischg, A. P., and Keiler, M.: Identifying spatial clusters of flood exposure to
705   support decision making in risk management. Science of the total environment, 598, 593-
706   603, https://doi.org/10.1016/j.scitotenv.2017.03.216, 2017.

707 Ruin, I., Gaillard, J. C., and Lutoff, C.: How to get there? Assessing motorists' flash flood risk
708   perception on daily itineraries. Environmental hazards, 7(3), 235-244,
709   https://doi.org/10.1016/j.envhaz.2007.07.005, 2007.

710 ~~Sallach, D. L., and Macal, C. M.: Introduction: The simulation of social agents. Social Science~~
711   ~~Computer Review, 19(3), 245-248, https://doi.org/10.1177/089443930101900301, 2001.~~

712 Shabou, S., Ruin, I., Lutoff, C., Debionne, S., Anquetin, S., Creutin, J. D., and Beaufils, X.:
713   MobRISK: a model for assessing the exposure of road users to flash flood events. Natural
714   Hazards and Earth System Sciences, 17(9), 1631, https://doi.org/10.5194/nhess-17-1631-
715   2017, 2017.

716 Shi, P.: Theory and practice of disaster study. Journal of Natural Disasters, 4, 8-19, 1996.

717 Terti, G., Ruin, I., Anquetin, S., and Gourley, J. J.: Dynamic vulnerability factors for impact-
718   based flash flood prediction. Natural Hazards, 79(3), 1481-1497.
719   https://doi.org/10.1007/s11069-015-1910-8, 2015.

720 Visual studio code: https://code.visualstudio.com/, 2018.

721 Wan, H., Wang, J.: Analysis of Public Adaptive Behaviors to Drought and Flood Disasters in
722   Middle Reaches of Weihe River:A Case Study on Qishan County of Shaanxi Province. Acta
723   Agriculturae Jiangxi, https://doi.org/10.19386/j.cnki.jxnyxb.2017.05.21, 2017.

724 Weis, S. W. M., Agostini, V. N., Roth, L. M., Gilmer, B., Schill, S. R., Knowles, J. E., and
725   Blyther, R.: Assessing vulnerability: an integrated approach for mapping adaptive capacity,
726   sensitivity, and exposure. Climatic Change, 136(3-4), 615-629,
727   https://doi.org/10.1007/s10584-016-1642-0, 2016.

728 Werren, G., Reynard, E., Lane, S. N., and Balin, D.: Flood hazard assessment and mapping in
729   semi-arid piedmont areas: a case study in Beni Mellal, Morocco. Natural Hazards, 81(1),
730   481-511, https://doi.org/10.1007/s11069-015-2092-0, 2016.

731 Yang, X., Yue, W., and Gao, D.: Spatial improvement of human population distribution based on
732   multi-sensor remote-sensing data: an input for exposure assessment. International journal of
733   remote sensing, 34(15), 5569-5583, https://doi.org/10.1080/01431161.2013.792970, 2013.

734 Yin, Z.: Research of urban natural disaster risk assessment and case study, Ph.D. thesis, East
735   china normal university, Shanghai, China, 2009.

736 Yin, J., Yu, D., and Wilby, R.: Modelling the impact of land subsidence on urban pluvial
737   flooding: A case study of downtown Shanghai, China. Science of the Total Environment,
738   544, 744-753, https://doi.org/10.1016/j.scitotenv.2015.11.159, 2016a.

739 Yin, W., Yu, H., Cui, S., and Wang, J.: Review on methods for estimating the loss of life
740   induced by heavy rain and floods. Progress in Geography, 35(2), 148-158,
741   https://doi.org/10.18306/dlkxjz.2016.02.002, 2016b.

742   **Figure 1.** Location of the study area (left) and a digital elevation model indicating the specific
743   details of the study area (right).

744   **Figure 2.** Overview of the dynamic exposure simulation to urban flooding.

745   **Figure 3.** Rainfall simulation results based on the CHM method, and observational data used for
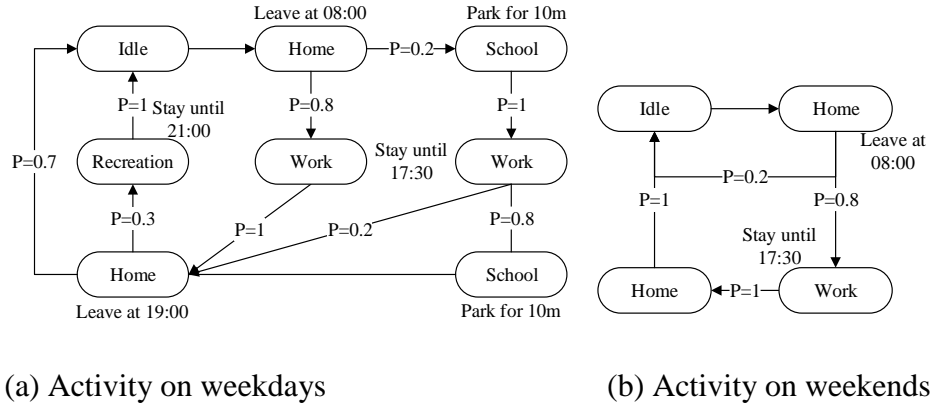746   fluvial flood simulation.

747   **Figure 4.** A synthetic daily routine generated from the travel survey and census data for an
748   employed male agent aged 18–60 years.

749   **Figure 5.** Activity patterns for an employed male agent aged 18–60 years and highly educated
750   during disaster scenarios. (a) Bad weather (weekday) (b) Warning (weekday) (c) Bad weather
751   (weekend) (d) Warning (weekend).

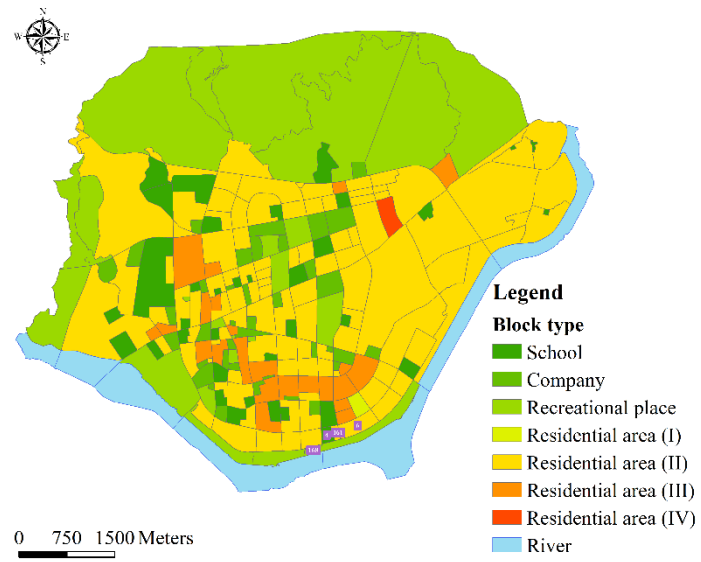752   **Figure 6.** Block numbers of different block types.

753   **Figure 7.** Spatial distribution of blocks.

754   **Figure 8.** Agent types for daily and disaster scenarios. Daily scenarios refer to S1, S2, S7, and S8.
755   Others are disaster scenarios.

756   **Figure 9.** Map of accumulated water depths and velocities. T means time here.

757   **Figure 10.** Changes in the surface water depths and velocities for eight severely flooded areas.
758   The "dep" indicates water depth, and "vel" indicates water velocity.

759   **Figure 11.** Map of the flooded area indicating the flooding simulation and the real flood in 2014.
760   The information for the flooded area was provided by Lishui City Housing and Urban-Rural
761   Construction Bureau.

762   **Figure 12.** Population changes in blocks and roads for the six scenarios.

763   **Figure 13.** Population distribution for the six scenarios. T means time here.

764   **Figure 14.** Changes in the population exposure of two blocks for the 12 scenarios. Block 168 was
765   a recreational area, and Block 6 was a residential area.

766   **Figure 15.** Changes in road and building exposures in severely flooded blocks. The exposed road
767   length and building area represent road and building exposures, respectively.

768   **Figure 16.** Map of road and building exposures. T means time here.

769
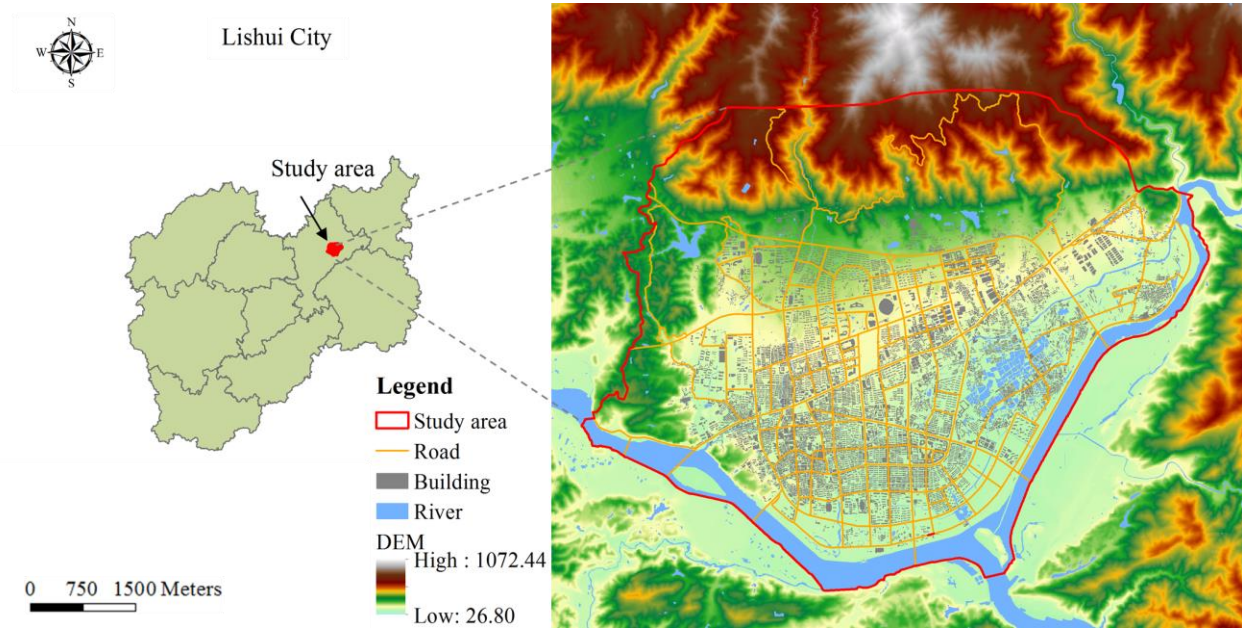
770

771 **Figure 1.** Location of the study area (left) and a digital elevation model indicating the specific
772 details of the study area (right).
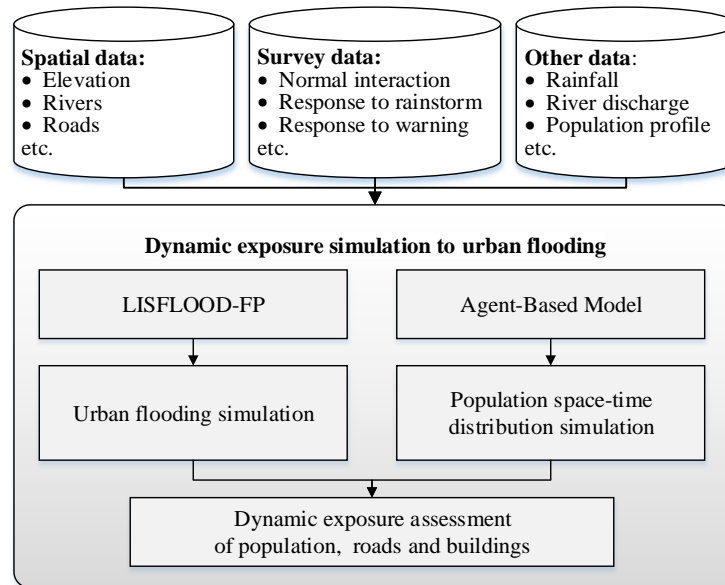
773

774   **Figure 2.** Overview of the dynamic exposure simulation to urban flooding.
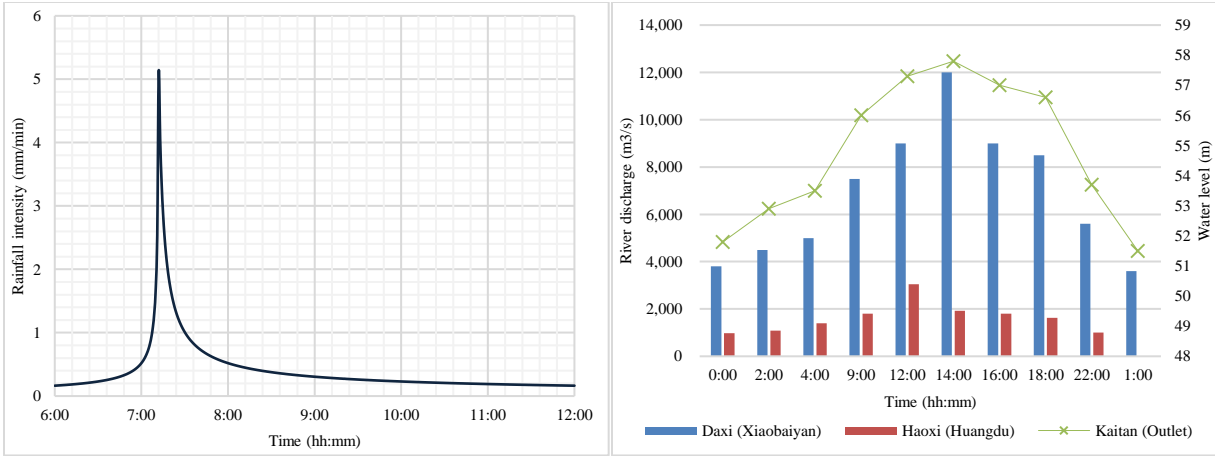
| 775 | |
| 776 | (a) Rainfall simulation data　　　　　(b) Observational data |

Figure 3. Rainfall simulation results based on the CHM method, and observational data used for fluvial flood simulation.

779

780   (a) Activity on weekdays   (b) Activity on weekends

781 **Figure 4.** A synthetic daily routine generated from the travel survey and census data for an

782 employed male agent aged 18–60 years.

783

784   (a) Bad weather (weekday)   (b) Warning (weekday)

785
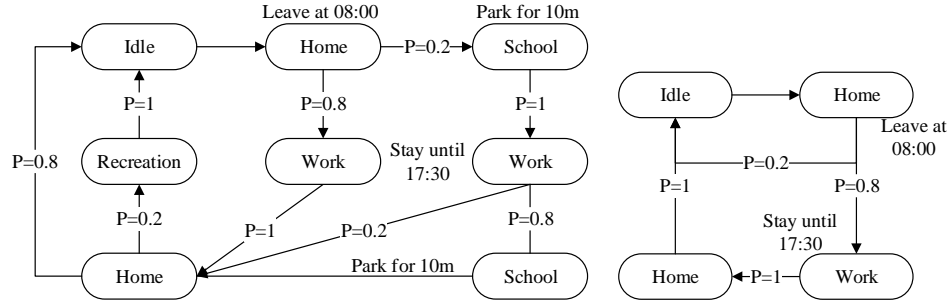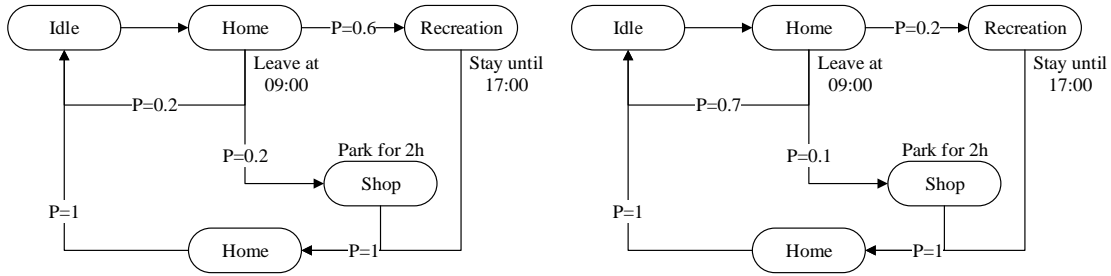
786   (c) Bad weather (weekend)   (d) Warning (weekend)

787 **Figure 5.** Activity patterns for an employed male agent aged 18–60 years and highly educated

788 during disaster scenarios. (a) Bad weather (weekday) (b) Warning (weekday) (c) Bad weather

789 (weekend) (d) Warning (weekend).

790

791
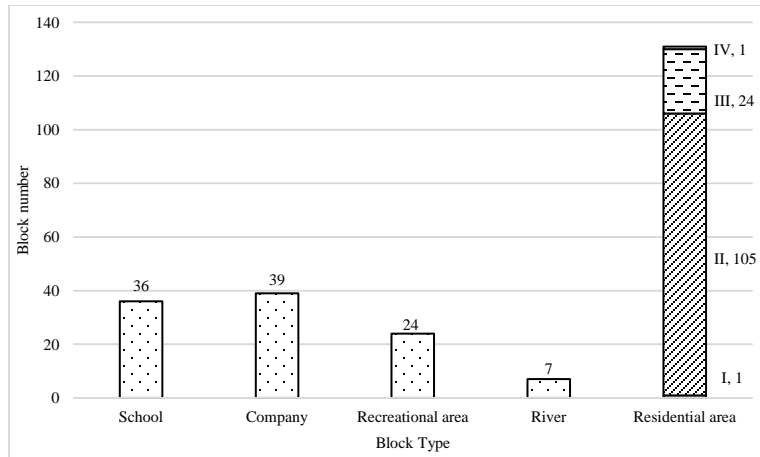
Figure 6. Block numbers of different block types.

Figure 7. Spatial distribution of blocks.

796
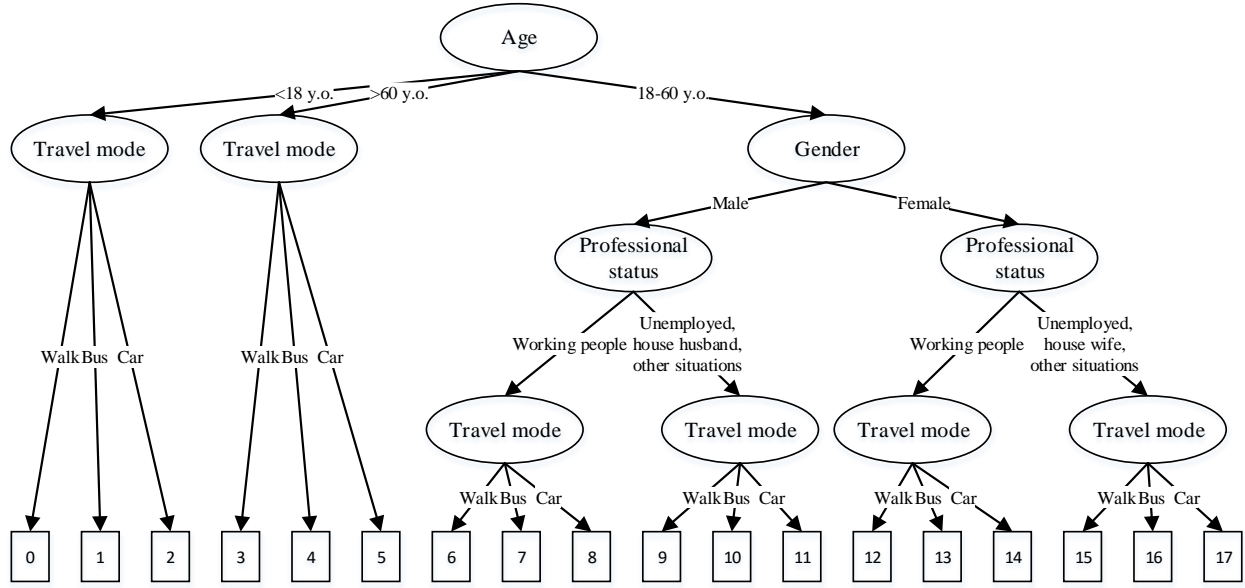
797
(a) Agent types for daily scenarios

798
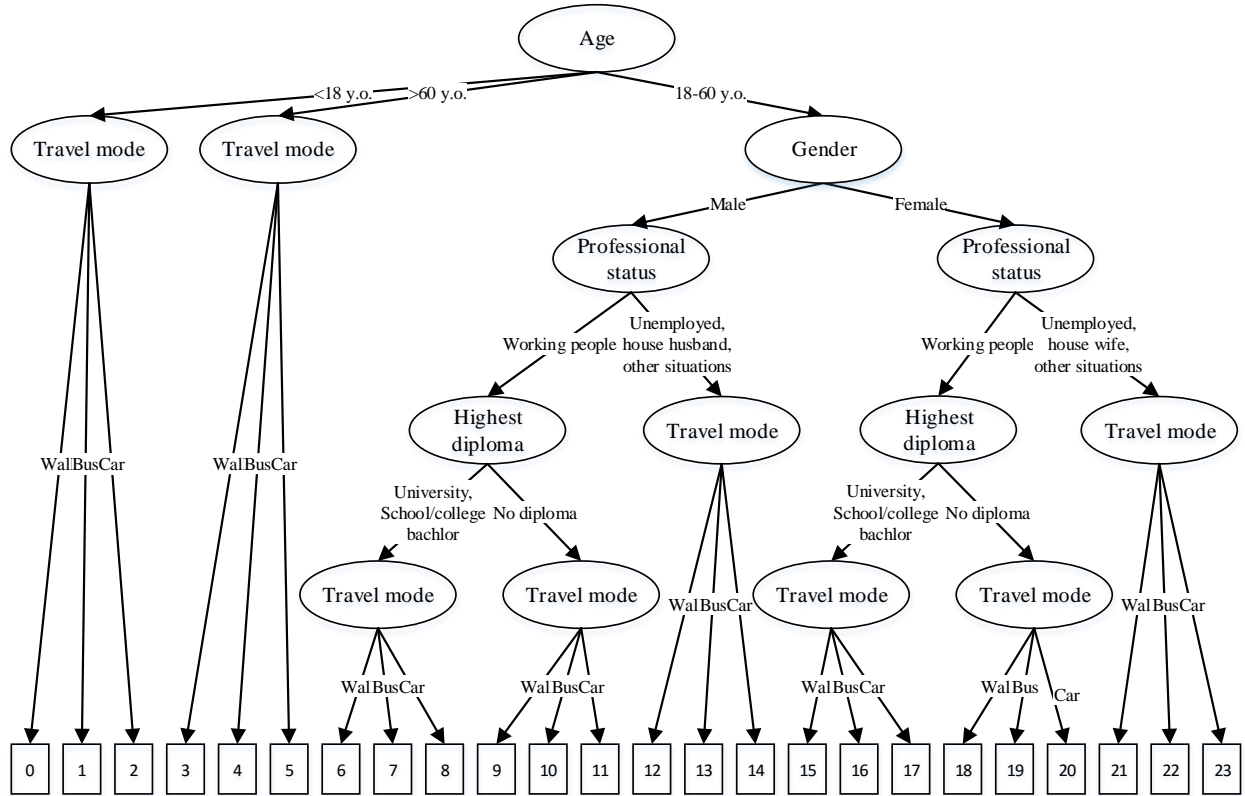
799
(b) Agent types for disaster scenarios

800 **Figure 8.** Agent types for daily and disaster scenarios. Daily scenarios refer to S1, S2, S7, and

801 S8. Others are disaster scenarios.

802
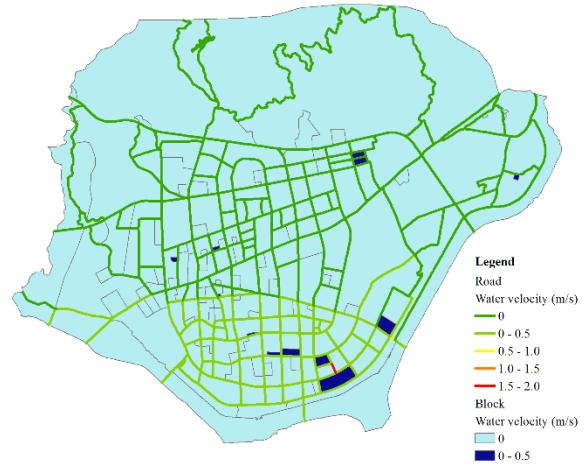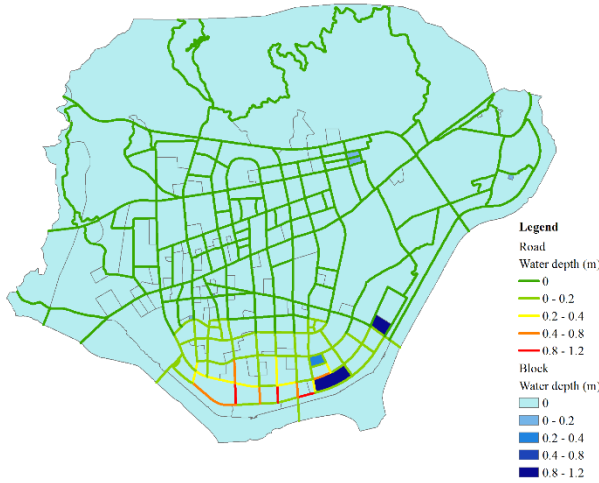
803   (a) Water depth (pluvial flood, T = 15:00)   (b) Water velocity (pluvial flood, T = 08:00)

804
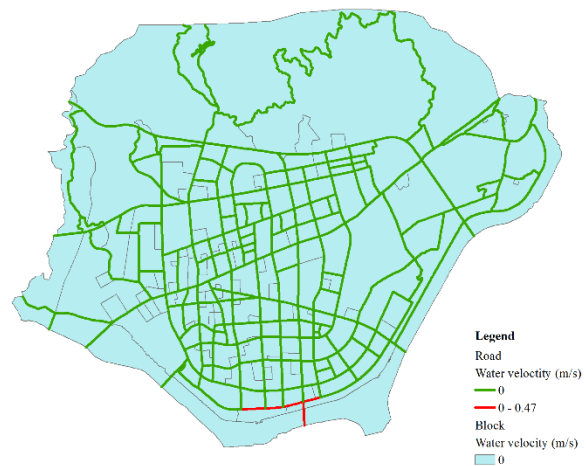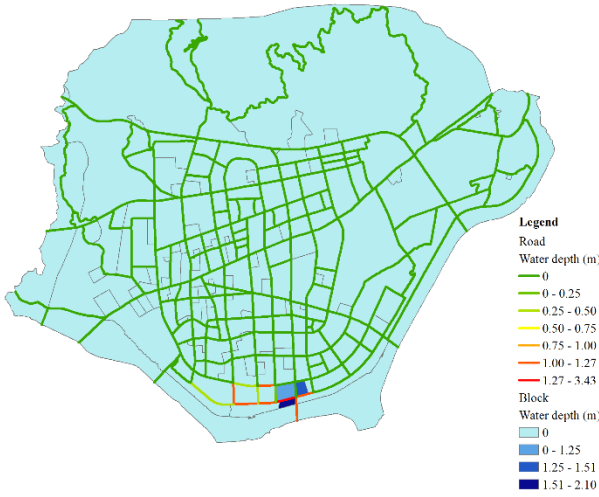
805   (c) Water depth (fluvial flood, T = 16:00)   (d) Water velocity (fluvial flood, T = 16:00)

806   **Figure 9.** Map of accumulated water depths and velocities. T means time here.

42

807

808   (a) Pluvial flood   (b) Fluvial flood

809   **Figure 10.** Changes in the surface water depths and velocities for eight severely flooded areas.

810   The "dep" indicates water depth, and "vel" indicates water velocity.

811
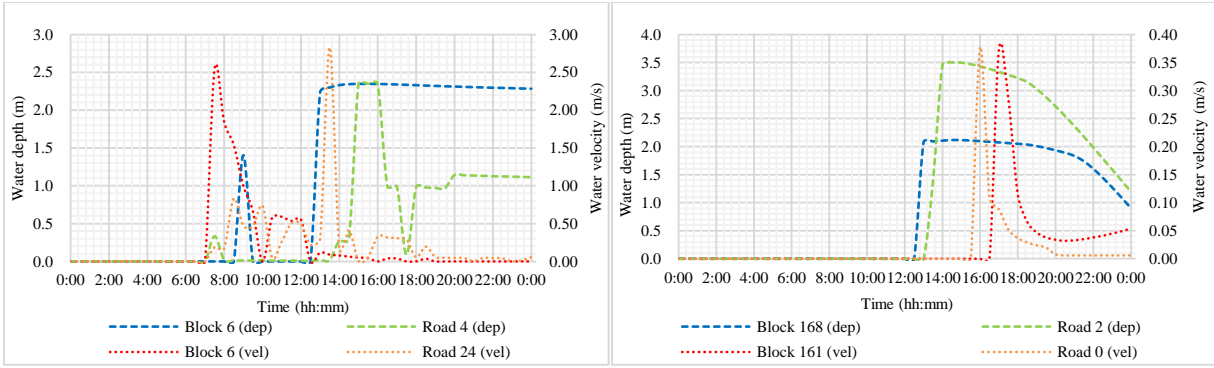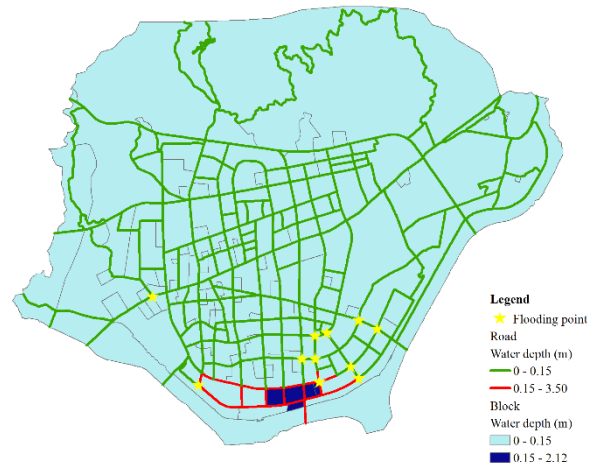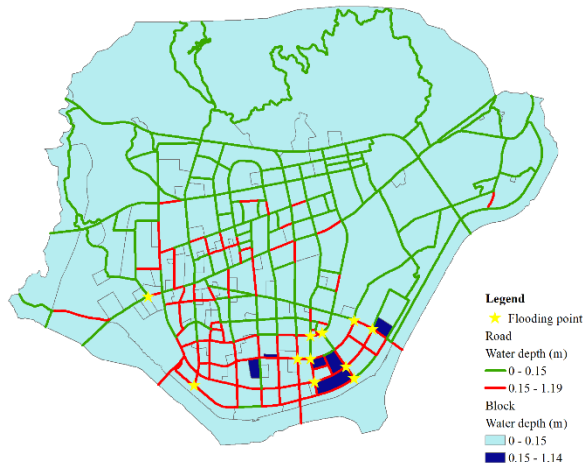
812   (a) Pluvial flood   (b) Fluvial flood

813   **Figure 11.** Map of the flooded area indicating the flooding simulation and the real flood in 2014.

814   The information for the flooded area was provided by Lishui City Housing and Urban-Rural
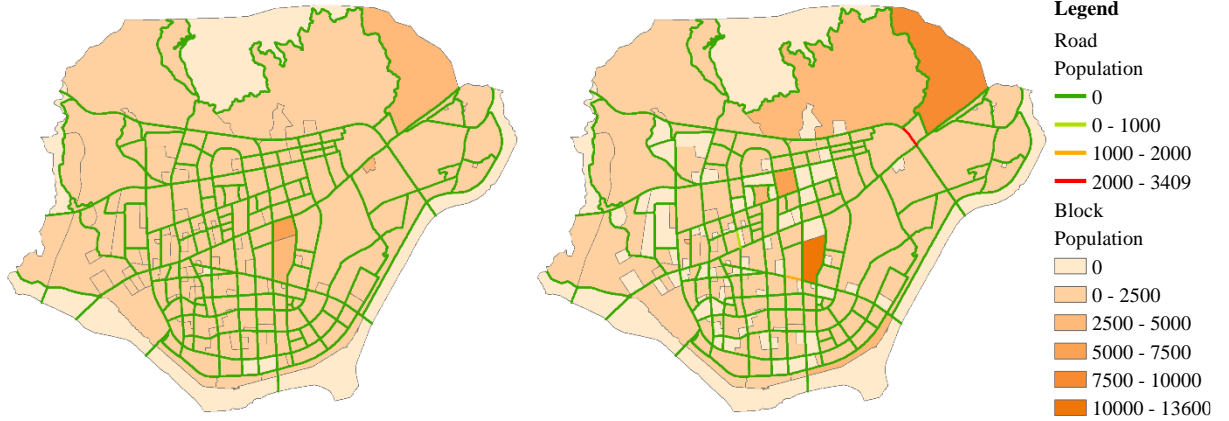
815   Construction Bureau.
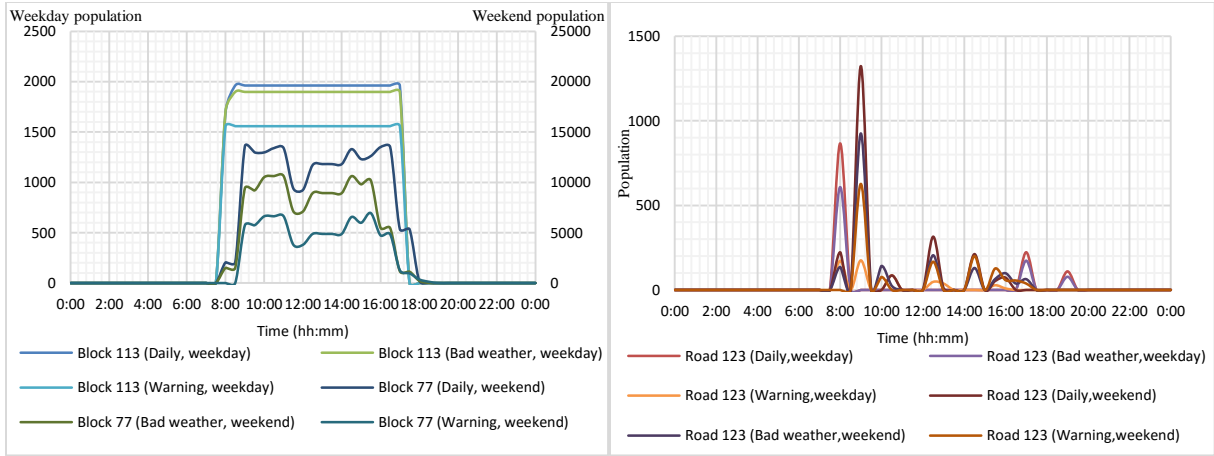
816

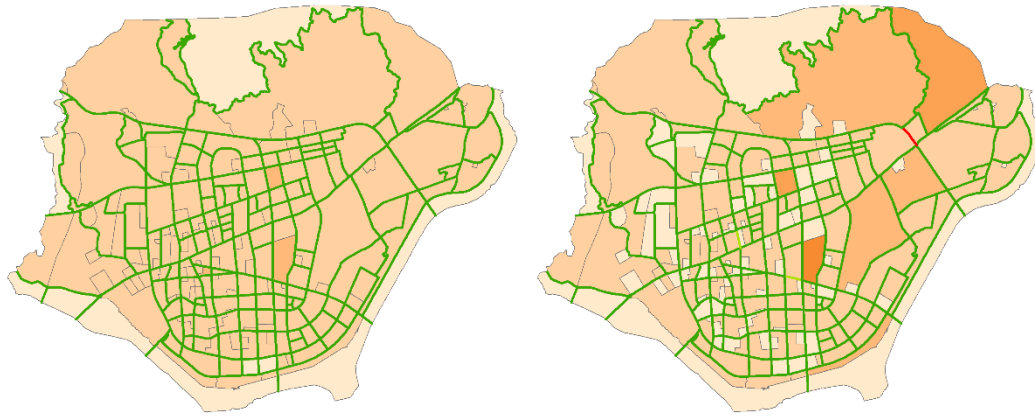817   (a) Block   (b) Road

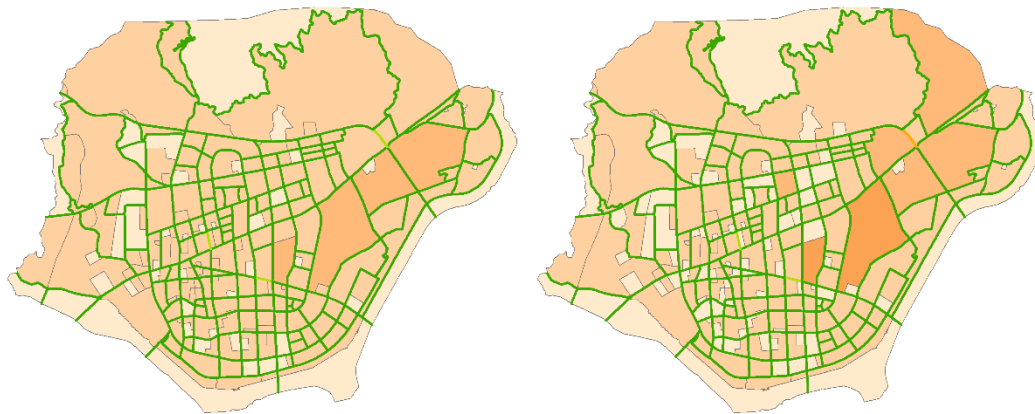818   **Figure 12.** Population changes in blocks and roads for the six scenarios.

819

820   (a) Daily, weekday (T = 09:00)   (b) Daily, weekend (T = 09:00)

821

822   (c) Bad weather, weekday (T = 09:00)   (d) Bad weather, weekend (T = 09:00)
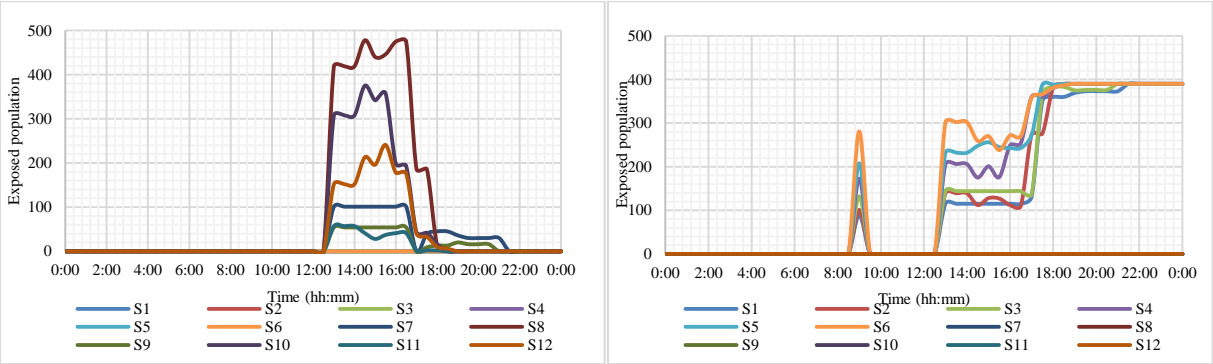
823

824   (e) Warning, weekday (T = 09:00)   (f) Warning, weekend (T = 09:00)

825   **Figure 13.** Population distribution for the six scenarios. T means time here.
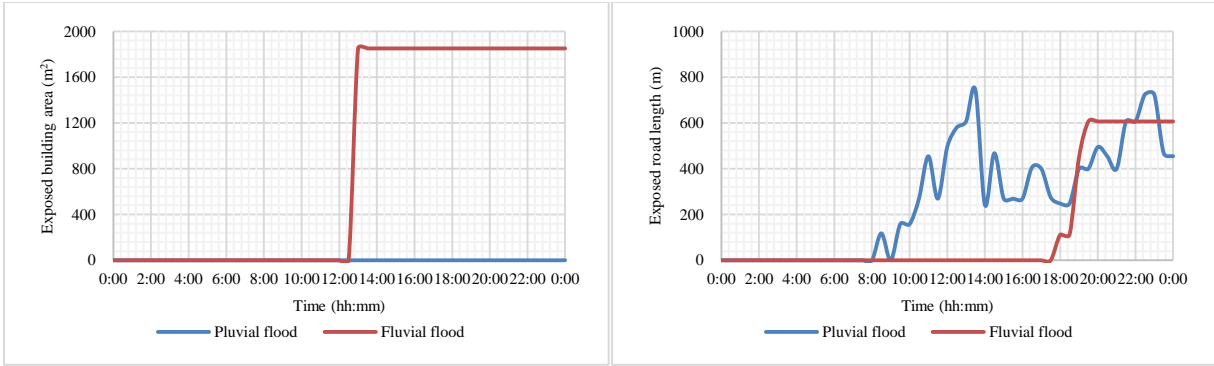
826

827

828   (a) Population exposure (Block 168)   (b) Population exposure (Block 6)

829   **Figure 14.** Changes in the population exposure of two blocks for the 12 scenarios. Block 168

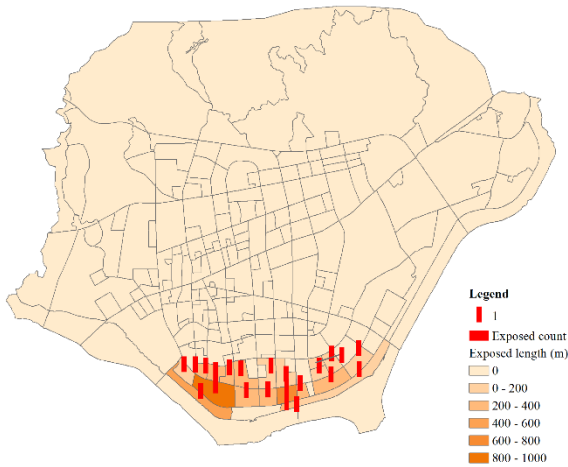830   was a recreational area, and Block 6 was a residential area.

831

832   (a) Exposed building area (Block 168)   (d) Exposed road length (Block 6)

833   **Figure 15.** Changes in road and building exposures in severely flooded blocks. The exposed road

834   length and building area represent road and building exposures, respectively.

835
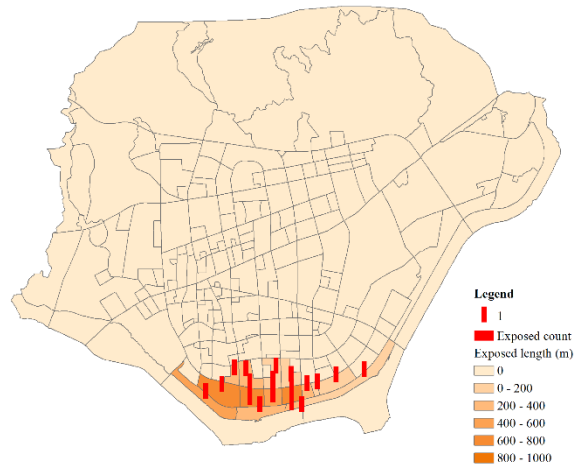
(a) Road exposure (pluvial flood, T = 18:30)   (b) Road exposure (fluvial flood, T = 18:30)

837
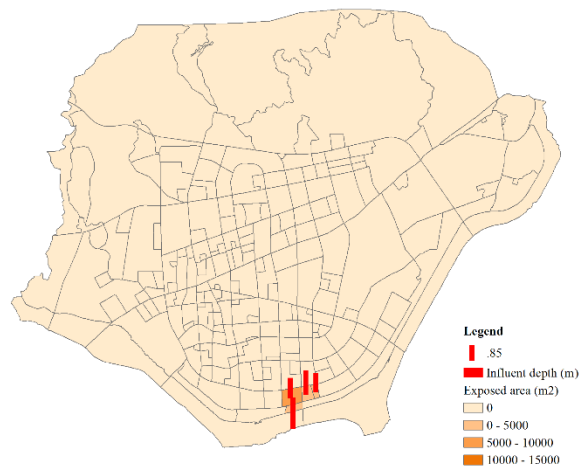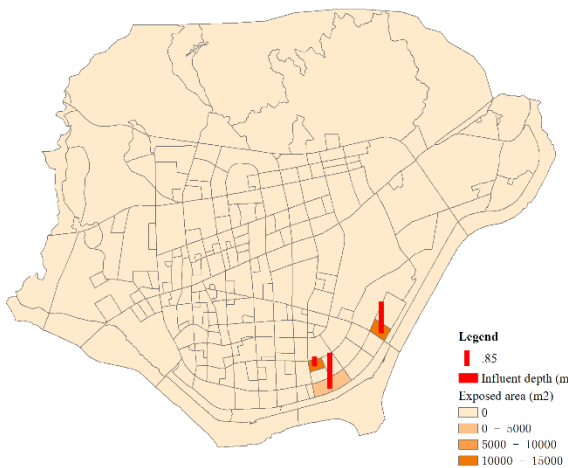
(c) Building exposure (pluvial flood, T = 18:30) (d) Building exposure (fluvial flood, T = 18:30)

Figure 16. Map of road and building exposures. T means time here.

840   **Table 1** Data used in this study.

841   **Table 2.** Parameter values for the rainstorm intensity formula.

842   **Table 3.** Parameter variations used in the simulation scenarios.

843   **Table 4.** Sociodemographic characteristics of the study area population.

844   **Table 5.** Building step heights for different block types.

Table 6. Traffic flow and population simulation results during peak hours on weekdays.

Table 7. Traffic flow and population simulation results during peak hours on weekends.

845   **Table 1.** Data used in this study.

Data	Source	Time	Use
Digital elevation model	Local government	2013	Topography (regular square grids with a 5 m resolution)
Basic geographic data	Local government	2015	Locations of rivers, roads, and buildings
Hydrological data	Local government	Aug 20, 2014	River discharge and water level
1 km grid population data	National Earth System Science Data Sharing Infrastructure, National Science & Technology Infrastructure of China (http://www.geodata.cn)	2010	Number of residents per grid in the study area
Population profile	Lishui Statistical Yearbook and Liandu Yearbook (http://tjj.lishui.gov.cn)	2014	Gender, age, education level, employment, and travel mode profiles were used to classify agent groups
Travel survey data	Face-to-face questionnaire surveys	July 8, 2018 to July 14, 2018	Social characteristics and daily activities of 500 residents
Traffic flow data	Local government	June 24, 2017 to July 7, 2017	Number of vehicles passing through a node within one hour at four intersections from June 24, 2017 to July 7, 2017 in this area
Water accumulation points	Local government (http://www.zjjs.com.cn)	Aug 20, 2014	Location

846

847   **Table 2**. Parameter values for the rainstorm intensity formula.

Parameter	Value
A	1265.3
b	5.919
c	0.587
n	0.611

848

849 **Table 3**. Parameter variations used in the simulation scenarios.

Scenarios	Flooding type	Human behavior	Weekdays or weekends
S1	Pluvial flood	Daily	Weekdays
S2	Pluvial flood	Daily	Weekends
S3	Pluvial flood	Bad weather	Weekdays
S4	Pluvial flood	Bad weather	Weekends
S5	Pluvial flood	Warning	Weekdays
S6	Pluvial flood	Warning	Weekends
S7	Fluvial flood	Daily	Weekdays
S8	Fluvial flood	Daily	Weekends
S9	Fluvial flood	Bad weather	Weekdays
S10	Fluvial flood	Bad weather	Weekends
S11	Fluvial flood	Warning	Weekdays
S12	Fluvial flood	Warning	Weekends

850

851   **Table 4**. Sociodemographic characteristics of the study area population.

Variables	Groups	Percentage (%)
Gender	Male	50.43
	Female	49.57
Age	0-17	18.73
	18-60	63.34
	>60	17.93
Professional status	Employed	55.77
	Unemployed	44.23
Education level	University, school-college, bachelor	14.46
(Highest diploma)	No diploma	85.54
Travel mode	Walk	25.24
	Bus	43.06
	Car	31.70

852   Note: Data are drawn from the 2015 Lishui Statistical Yearbook and 2015 Liandu Yearbook.

Table 5. Building step heights for different block types.

No	Block type	Building type	Building step height
1	Residential area I	Garden house, villa	0.35 m (with > 9 floors, 0.60 m)
2	Residential area II	High-rise apartments and new village houses (before 1988); new residential quarters and commercial houses (after 1988)	0.35 m (with > 9 floors, 0.60 m)
3	Residential area III	New and old lane homes, three types of staff housing	0.10 m
4	Residential area IV	Shed house	0.05 m
5	School	Educational building	0.35 m (with > 9 floors, 0.60 m)
6	Company	Office building	0.35 m (with > 9 floors, 0.60 m)
7	Recreational area	Public buildings for business, culture, sports, and other uses	0.35 m (with > 9 floors, 0.60 m)

853

Table 6. Traffic flow and population simulation results during peak hours on weekdays.

Road junction	Time	Sim.	Obs.	Deviation ratio
LQ-KF	8:00–9:00	319	366	-12.84%
LQ-KF	17:00–18:00	602	591	1.86%
LQ-HY	8:00–9:00	353	398	-11.31%
LQ-HY	17:00–18:00	740	731	1.23%
LQ-ZJ	8:00–9:00	381	369	3.25%
LQ-ZJ	17:00–18:00	824	814	1.23%
LT-ZJ	8:00–9:00	531	508	4.53%
LT-ZJ	17:00–18:00	994	938	5.97%

854

Table 7. Traffic flow and population simulation results during peak hours on weekends.

Road junction	Time	Sim.	Obs.	Deviation ratio
LQ-KF	8:00–9:00	523	529	-1.13%
LQ-KF	17:00–18:00	659	693	-4.91%
LQ-HY	8:00–9:00	761	725	4.97%
LQ-HY	17:00–18:00	822	790	4.05%
LQ-ZJ	8:00–9:00	651	638	2.04%
LQ-ZJ	17:00–18:00	825	873	-5.50%
LT-ZJ	8:00–9:00	778	712	9.27%
LT-ZJ	17:00–18:00	1083	1132	-4.33%

855