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

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8   **Abstract:**

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

10   disaster-bearing bodies within an event, and thus cannot satisfy the increasingly elaborative

11   modelling and management of urban flood. In this study, a comprehensive method was developed

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

13   flood 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 period of urban flooding. 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 the case study. The results indicated evident spatio-temporal variations in urban

18   flooding and population distribution. Additionally, the exposure increased with increasing rainfall

19   and flooding severity. The urban area near the Oujiang River was the most severely flooded and

20   indicated the largest amount of exposure of population, roads, and buildings. Furthermore, the

21   impacts of flooding on roads were greater than those on population and on buildings. This study

22   presents the first fully formulated method for dynamic urban flood exposure simulation at high

23   spatio-temporal resolution. The results of this study can provide baseline data for determining

24   urban flood disaster vulnerability, socioeconomic loss assessment, urban disaster risk management,

25   and for establishing emergency response plans.

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

1. Introduction

Storm flooding has become increasingly frequent and severe with the intensification of global warming and the rising frequency of extreme weather events (*Dankers and Feyen, 2008*; *Hammond et al., 2015*). Urban floods have become major natural disasters in many cities around the world and have created serious threats to human life and social and economic activities (*Gain et al., 2015*). Effectively coping with floods and their adverse effects is an important part of disaster prevention and mitigation as well as disaster risk management (*Atta-Ur-Rahman, 2014*). Non-engineering measures such as exposure assessment are currently the main way of managing urban flooding risk (*Chen et al., 2015*). Exposure refers to the presence of people, livelihoods, environmental services and resources, infrastructure, or economic, social, or cultural assets in places that could be adversely affected by natural disasters (*IPCC, 2012*). Urban flood disasters are caused by the adverse effects of heavy rain and other factors on the city system in certain disaster-pregnant environments. These events consist of three parts: the disaster-causing factors, the disaster-pregnant environment, and the disaster-bearing bodies (*Shi, 1996*).

Exposure has obvious dynamic characteristics because of the dynamic evolution of urban floods and disaster-bearing bodies. Therefore, the characteristics of flood disasters and building environments and the distribution of population and socio-economic resources are the key factors for evaluating urban flood exposure. The methods for evaluating exposure to urban flooding at a certain time or period vary due to changes in the disaster-bearing bodies, study areas, data acquisition methods, etc. (*Röthlisberger et al., 2017*). Index-based methods are commonly used

47   for comprehensive exposure evaluation (*Mahe et al., 2005*; *Mansur et al., 2016*; *Guo et al., 2014*).

48   Statistical methods based on historical disaster data are also utilized (*Moel et al., 2011*).

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

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

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

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

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

54   established, thus resulting in simulation results applicable only to macro planning and decision

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

56   heterogeneity and resolution.

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

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

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

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

61   research results. At the micro time scale, disaster-causing factors and disaster-bearing bodies

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

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

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

65   urban residents, such as commuting between residential and work or learning spaces, cause a

66   dynamic spatio-temporal distribution of the population. At the same time, the exposure to urban

67   flooding changes dramatically over a short period of time. To avoid or reduce disaster risks,

68   casualties, and property losses, different individuals are likely to adopt different adaptive behaviors,

69   such as delaying or cancelling travel plans, while the government is likely to adopt organizational

70   actions such as issuing warnings and evacuating residents (*Wan and Wang, 2017*; *Parker et al.,*

71   *1995*). Thus, the dynamic simulation of exposure requires the dynamic space-time simulation of

72   variations in the disaster, disaster-bearing bodies, as well as interactions between them. Modeling

73   of the temporal and spatial changes in natural disasters mainly uses the disaster system simulation

74   method, and the typical representative used is a hydrological or hydrodynamic model to simulate

75   flood disasters (*Werren et al., 2016*). The change simulation of the disaster-bearing body

76   (population) can use the method based on individual space-time mark data (*Liang et al., 2015*) and

77   the agent-based method (*Kang et al., 2012*). Although the former can acquire the human position

78   and moving track, it is difficult to identify the purpose of human activities, and human disaster

79   response behavior cannot be simulated. The agent-based model (ABM) can not only simulate the

80   population distribution but can also simulate the interaction among the population (as the disaster

81   victim), the hazard factors, and the disaster-pregnant environment (*Yin, et al., 2016b*). Current

82   research has used the ABM to simulate human responses to disasters, which, in turn, have been

83   used in natural disaster risk research (*Johnstone, 2012*; *Huang et al., 2015*). Nevertheless, the

84   simulation results do not reflect the exposure characteristics of the disaster-bearing bodies and

85   their dynamic changes (*Dawson et al., 2011*).

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

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

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

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

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

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

92   applied to an urban area as a case study. Exposure simulation is a useful tool for estimation of

93   disaster vulnerability and assessment of losses, and the results of this study are likely to benefit

94   the relevant government agencies in assessing risk, issuing warnings, and planning emergency

95   responses to urban natural disasters.

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

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

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

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

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

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

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

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

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

105   The datasets used in this study included a digital elevation model and data for rivers, roads,

106   buildings, population, and observation data consisting of flow and water level. Traffic flow and

107   water accumulation data were used for validation. Table 1 describes the sources and uses of the

108   datasets.

109   **3. Methodology**

110   This study comprised three aspects: disaster simulation, human activity simulation, and dynamic

111   exposure assessment (Fig. 2). The first step included fluvial and pluvial flooding simulation based

112   on the LISFLOOD-FP model. The simulation of human activity utilized ABM to obtain the spatio-

113   temporal distribution of the population under different scenarios. Finally, the developed model

114   was combined with the results of the previous two steps to assess the dynamic exposure of the

115   population, roads, and buildings to urban flooding.

116   **3.1 Flood models**

117   A wide variety of existing hydrological or hydrodynamic models are available that are capable of

118   simulating fluvial or pluvial flooding, including the Storm Water Management Model (SWMM)

119   (*Rossman, 2015*), LISFLOOD (*Bates and De Roo, 2000*), MIKE-SHE (*DHI, 2000*), MIKE-11

120   (*Havnø et al., 1995*), MOUSE (*Lindberg et al., 1989*), HEC-RAS (*Brunner, 2008*), and HEC-HMS

121   (*Charley et al., 1995*). LISFLOOD-FP (*Bates et al., 2013*) is a coupled 1D/2D hydraulic model

122   based on a raster grid and was designed for research purposes at the University of Bristol.

123   LISFLOOD-FP uses a square grid as the computational grid to simulate one-dimensional river

124   hydraulic changes and two-dimensional floodplain hydraulic changes. The applicability of the

125   model has been verified by several studies (*Horritt and Bates, 2002*; *Bates and De Roo, 2000*).

126   Therefore, the LISFLOOD-FP model was chosen for the simulation of fluvial and pluvial flooding.

127   Floodplain flows were described in terms of the continuity and momentum equations discretized

128   over a grid of square cells, which allowed the model to represent 2D dynamic flow fields for the

129   floodplain. It assumed that the flow between two cells was simply a function of the free surface

130   height difference between those cells:

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

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

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

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

135   the volumetric flow rates between the floodplain cells. Q_y is defined analogously to Q_x. The flow

136   depth, h_{flow}, represents the depth through which water can flow between two cells, and d is

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

138   highest bed elevation.

139   The types of flooding simulated in this study included pluvial and fluvial floods. Synthetic rainfall

140   data for a return period of 50 years used for pluvial flood simulation were simulated using the

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

142   the rainstorm intensity formula (Eq. (3)), rainfall duration time (T), and peak position (r).

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

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

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

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

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

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

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

150   which is related to the return period. The rainfall duration was 6 hours (6 am to 12 pm), and the

151   accumulated rainfall was nearly 148 mm. Here, we fixed r at 0.2 based on the assumption that the

152   peak is located at the one fifth point of the design hyetograph. The parameters A, b, c and n were

153   estimated from the rainstorm intensity formula for Lishui City obtained from the "Zhejiang City

154   Rainstorm Intensity Formula Table" published by the Hangzhou Municipal Planning Bureau

155   (Table 2). The rainfall simulation results are shown in Fig. 3(a). The flow and water level input

156   data for fluvial flood simulation utilized observational data from Lishui's 50-year flood in 2014,

157   provided by the Liandu Hydrological Station (Fig. 3(b)). The flow data for the Daxi and Haoxi

158   rivers on August 20, 2014 were obtained from the Xiaobaiyan and Huangdu stations, respectively,

159   and the observational data for water levels at the outlets were those for the Kaitan Dam.

160   **3.2 ABM**

161   Several modeling techniques, often collectively referred to as social simulation, have been

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

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

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

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

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

167   capture interactions and dynamic responses in a spatial environment.

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

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

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

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

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

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

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

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

176   predicted just by aggregating individual agent behaviors.

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

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

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

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

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

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

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

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

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

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

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

188 flood warning times, and evacuation strategies.

189 **3.3 Spatio-temporal simulation of population distribution**

190 The individual travels were simulated using ABM by defining the activity patterns of different

191 types of residents to subsequently obtain the distribution of the population at each moment. The

192 ABM of residents' travels established in this study included two core elements of agents and

193 activities, and two basic elements of blocks and networks. The travel survey data were used

194 according to the demographic properties of the agent to generate synthetic daily routines.

195 Residents were independent individuals with subjectivity. This study abstracted them as agents.

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

197 types of agents were classified according to the social characteristics of the residents. Age and

198 gender characteristics mainly affect the ability of people to respond to disasters. The self-help

199   abilities of the minors under 18 years of age and residents older than 60 years are generally poor.

200   In the event of natural disasters, they are generally categorized as the objects of help. The middle-

201   aged group (18–60 years old) generally has greater physical strength with better ability to cope

202   with disasters. Unemployed people are more vulnerable to natural disasters. On the one hand, their

203   living environments and resistance to disasters are poor; on the other hand, their economic

204   conditions are limited, which impedes recovery after the disaster and seriously affects their daily

205   life in the short term. Education level is related to the possibility of receiving early warning

206   information by the individual. Individuals with higher education levels are more likely to respond

207   to early warning information and are more aware of disasters than others (*Terti et al., 2015*; *Shabou*

208   *et al., 2017*). Additionally, different travel modes have different effects on the activity patterns of

209   people as well as on exposure levels when disasters occur. Therefore, the agent types were divided

210   according to age, gender, employment status, education level, and travel mode.

211   Activities were classified as work, learning, leisure, recreation, shopping, rest, and travel. An

212   activity pattern consisted of a series of activities to describe the spatio-temporal distribution of the

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

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

215   activity patterns in different scenarios. To capture the variability in the travel survey and the

216   uncertainties in behavior, synthetic daily routines were described in probabilistic terms. Figure 4

217   presents an example of the synthetic daily routine of an agent with the following demographic

218   characteristics: female agent, aged 18–60 years, and unemployed. In this example, the agent started

219   the day at 8 am on a weekday. The agent then traveled by a school to drop the children off,

220   subsequently had a 0.8 probability of shopping, and so on.

221   The study area was discretized into several blocks to improve the spatial resolution of the exposure

222   results. The discretization procedure was conducted with geographic information system (GIS)

223   tools (*Lü et al., 2018*), and several factors, including rivers, roads, land use, and buildings, were

224   considered. Blocks were activity places for agents and represented the smallest unit of exposure.

225   This study divided the block into five categories: residential area, school, company, recreational

226   area, and others. Additionally, the residential areas were subdivided into I, II, III, and IV classes

227   according to the type of building.

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

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

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

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

232   Although various factors are involved in the route choice process, several studies have indicated

233   that minimizing travel time is the principal criterion for selecting routes (*Papinski et al., 2009*;

234   *Ramming, 2001*; *Bekhor et al., 2006*). Therefore, the classical Dijkstra algorithm, a single-source

235   shortest path algorithm that provides trees of minimal total length and time in a connected set of

236   nodes, was selected in this study (*Dijkstra, 1959*). The activity pattern attributions concerned only

237   the starting times and durations of the activity sequences, thus indicating that the travel duration

238   for each individual was computed based on the distance between the different activity locations.

239   Therefore, the implemented schedules may be distorted compared to the assigned schedules in

240   terms of travel durations (*Terti et al., 2015*).

241   **3.4 Impacts of disasters on anthropogenic activities**

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

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

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

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

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

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

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

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

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

251   behavior of residents to disaster events.

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

253   patterns and their changing probabilities. Figure 5 indicates activity patterns for unemployed adult

254   women during different disaster scenarios. The "bad weather" scenario was similar to the "daily

255   activity" pattern. For instance, the change in travel probability during "bad weather" due to a

256   rainstorm reflected the adaptive behavior of residents. The "warning" scenario assumed that the

257   government had issued early warning information at eight a.m., the schools had suspended classes

258   during the weekday, and the resident responses were stronger than those to the "bad weather"

259   scenario, thereby resulting in a greater difference in activity patterns.

260   **3.5 Dynamic exposure assessment**

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

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

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

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

265   (i) Population

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

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

268   population and accounted for vulnerable groups and road users. Among these, age was the primary

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

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

271   (ii) Roads

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

273   freight transportation but also disaster-bearing bodies (*Yin, et al., 2016a*), as they are vulnerable

274   to flood disasters. This study selected the number and lengths of exposed roads to reflect road

275   exposure.

276   (iii) Buildings

277   The aggravation of urban flooding has made building flooded more common in urban areas, thus

278   resulting in loss of internal property and construction structure. Additionally, the dynamic state of

279   building exposure is related to the safety of both the building as well as the nearby population. In

280   this study, the area of the exposed building and the depth of accumulated water in the building

281   were considered to be the building exposure.

282   **3.6 Scenario design**

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

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

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

286   12 scenarios, representing different flooding types and human activities, were designed in this

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

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

289   **4.   Results**

290   **4.1 Model implementation and parameter setting**

291   As an important spatial data management and analysis technology, GIS plays an important role in

292   dynamic exposure analysis of urban floods. Because of the simplicity, readability and extensibility

293   of the Python programming language, an increasing number of research institutes are adopting it

294   for development. Therefore, the model was developed using the Visual Studio Code software

295   (*Visual studio code, 2018*) and Python programming language (*Python, 2018*). The development

296   of the graphical user interface (GUI), GIS module, and drawing module was realized by Qt (*Qt,*

297   *2018*), Geopandas (*Geopandas, 2018*), and Matplotlib (*Matplotlib, 2018*), respectively.

298   (i) Block generation

299   In this study, the study area was divided into 237 blocks based on the method introduced in Sect.

300   3.3. The block types and their spatial distributions are shown in Fig. 6 and Fig. 7, respectively.

301   Most of the blocks in the study area were categorized as residential area, while blocks of

302   recreational areas and others (which indicated rivers) were few and concentrated.

303   (ii) Parameter setting

304   Since the census did not identify individuals according to addresses, at the start of each simulation,

305   an agent population with the same distributions of age, gender, employment, education level, and

306   travel mode was randomly located within the residential area for the case study. The synthetic

307   daily routines were described in probabilistic terms to capture the variability in the travel survey

308   and uncertainties in behavior.

309   Additionally, to reduce the number of agent types, only a limited number of agent classifications

310   were used. The distribution of population characteristics for Liandu District is shown in Table 4.

311   The agents were divided into 18 types for daily (non-disaster) scenarios and 24 types for disaster

312   scenarios based on the influence of education level on the individual disaster response behavior

313   (Fig. 8).

314   (iii) Exposure threshold

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

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

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

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

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

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

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

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

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

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

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

326   mortality (which is subject to random factors as well as those mentioned previously), exposure to

327   floodwater depths of 25 cm or greater under relatively fast flowing (2.5 m/s or greater) conditions

328   was established as the threshold for most vulnerable people (*DEFRA and Environment Agency,*

329   *2003*). This provided a conservative estimate of individuals vulnerable to floodwater rather than

330   an estimate of mortality (*Dawson et al., 2011*).

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

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

333   reducing the exposure of the building. Therefore, this study assigned building step heights to

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

335   conditions of the study area (Table 5). It should be noted that the block type "Other" constituted

336   rivers and did not contain buildings. Therefore, the exposure of the building was determined

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

338   entering the building was the difference between the depth of the flood and the height of the step.

339   **4.2 Flood simulation**

340   Figure 9 indicates the accumulated water depths and velocities of pluvial and fluvial floods in the

341   study area. As is evident, the pluvial and fluvial floods exerted significant impacts, and the urban

342   area near the Oujiang River was the most severely flooded area. Additionally, water is also

343   accumulated in the inner areas of the city, mainly on roads, in case of pluvial flood disasters. The

344   variations in water depths and velocities for eight severely flooded areas (including blocks and

345   roads) are presented in Fig. 10. As indicated, evident spatio-temporal variations in flooding were

346   observed. Figures 9 and 10 indicate that water depth was the main factor causing life and property

347   losses, whereas water velocity had little or no effect.

4.3 Simulation of the spatio-temporal distribution of population

The population spatio-temporal distribution was simulated based on six scenarios: (1) daily, weekday (S1, S7); (2) daily, weekend (S2, S8); (3) bad weather, weekday (S3, S9); (4) bad weather, weekend (S4, S10); (5) warning, weekday (S5, S11); (6) warning, weekend (S6, S12). Figure 10 indicates the population variation for blocks and roads for the six scenarios. Figure 11(a) indicates that, among the three weekend scenarios, the population in the playground (Block 77) changed more than the population in the company (Block 113). Figure 11(b) indicates that the population on the roads was volatile, and the morning peak hour during the weekend was delayed by an hour in comparison to that during the weekdays. The population distribution in the study area is shown in Fig. 12. The population was unevenly distributed and concentrated in recreational and residential areas over the weekend. However, the population distribution on weekdays was relatively uniform. The concurrent population distribution for the six scenarios changed significantly during the weekend, while the distribution for weekdays changed little.

Figures 11 and 12 indicate that the population change patterns were different for different blocks types. The daily routines of several people started from the residential area (home) in the morning, followed by school or company blocks during weekdays and recreational areas during weekends, and, finally, concluded with a return to the residential area at night. During the occurrence of rainstorms or the reception of warning messages, different types of people reacted differently (continuing, postponing, or cancelling the originally planned activities). Vulnerable people, like the elderly and children, and sensitive people (such as the homeless) were more likely to cancel travel plans. Additionally, recreational activities were more likely to be cancelled than were learning and work activities.

4.4 Exposure assessment

370

371   Figure 13 presents the population exposure variation for two selected areas. The difference

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

373   degrees of water accumulation. Figure 13(a) indicates that population exposure was the highest for

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

375   as indicated in Fig. 13(b), the population was most exposed to both weekend and weekday warning

376   scenarios. This is attributed to the assumption that the disaster response behavior adopted by

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

378   the response was not based on the exposure of the residential area. Therefore, when residential

379   areas, such as Block 6, were exposed to floods, the residents chose to reduce travel, thus resulting

380   in an increase in the population of residential areas and consequently increasing the population

381   exposure. According to the analysis of the 12 scenarios, the government departments can carry out

382   disaster prevention and mitigation measures for areas with large amounts of population exposure,

383   such as evacuation prior to the disaster, and initiate key rescue operations during the disaster. The

384   method proposed in this study can also help determine vulnerable populations and road users in

385   the exposed blocks. Because we had considered vulnerable people and road users when we

386   constructed the population groups (agents), we can get similar information from the results of

387   vulnerable populations and road users in the exposed blocks, like the exposed population. Such

388   information is of great practical significance.

389   Figure 14 presents variations in the road and building exposures of two selected areas with serious

390   flooding. The road and building exposures for the study area are presented in Fig. 15. It can be

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

392   flood depth. Additionally, the exposed road length of the block was fluctuant, while the building

393   was either entirely exposed or not exposed. Furthermore, the area of the road affected by pluvial

394   and fluvial floods was greater than that of the buildings. As indicated in Fig. 15, exposed buildings

395   were present only in a few areas (blocks), while roads were affected in several areas. Additionally,

396   buildings were least exposed due to high thresholds or the number of building steps designed and

397   built in recent years, while roads and population were severely affected by floods.

398   **4.5 Validation**

399   The flooded urban roads and locations in Lishui during the 50-year flood in 2014 were as follows:

400   the city had 10 flooded roads and 18 water accumulation points. The actual hydrological points

401   were selected and combined with the urban flooding results simulated by the prototype system.

402   The water accumulation distribution is indicated in Fig. 16.

403   To avoid overlapping with the simulated water accumulation results for roads, the actual flooding

404   points in the figure only included road junctions and the entirety of Gucheng road (the Lutang

405   Street to Dayou Street section), and Liyang Street (which connected the senior middle school to

406   the Sanyan temple section) was represented by corresponding intersection points. Figure 16

407   indicates that both the simulation results and the actual water accumulation points were mainly

408   distributed along the river. The simulated water accumulation area (Fig. 16(a)) included roads in

409   the center of the city and was larger than the actual flooding area. This difference could be

410   attributed to different definitions of "water accumulation". The simulation results presented in

411   Figure 16 included all areas where the accumulated water depth during the flooding period was

412   greater than 15 cm. The actual water accumulation point was defined as one experiencing rainfall

413   greater than 50 mm over a 24 hour period. Additionally, it was characterized by the water

414   accumulation depth of the road reaching 15 cm (the meteorological department issued the blue

415   rainstorm warning at this level), the water withdrawal time reaching one hour, and the water

416   accumulation scope value being greater than 50 m^2. Certain gaps existed between the observational

417   data and the actual flow since the observation station was far from the study area. Hence, the results

418   indicated that the simulated water accumulation area during the fluvial flood (Fig. 16 (b)) was

419   smaller than that of the actual situation.

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

421   verified by utilizing the traffic flow data from June 24 to July 7, 2017. The morning and evening

422   peak hours on weekdays and weekends, the simulated total number of residents passing the four

423   intersections (such as the junction of the Liqing and Huayuan roads) during peak hours, and the

424   actual measured traffic flow at the intersections are shown in Fig. 17. The traffic flow data in Fig.

425   17 are multi-day average results.

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

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

428   as indicated in Fig. 17, the simulated value was close to the measured value. This could be

429   attributed to the assumption that the study area was closed and the simulated population was the

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

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

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

433   population. Therefore, the number of pedestrians on the road was small. However, both the

434   simulated and measured values were essentially similar with regard to changes in their trends.

435   Therefore, the simulation method for the spatio-temporal distribution of population is feasible, and

436   the results are reliable.

5. Conclusions

Urban flooding considerably impacts the daily lives of residents and not only affects commuting but also causes casualties and traffic congestion. This study proposed a method for obtaining high-resolution dynamic exposure to urban flooding. First, the spatio-temporal distributions of pluvial and fluvial floods were simulated by the LISFLOOD-FP model. Second, the responses of residents to bad weather and government measures (warnings) were incorporated to develop an ABM to simulate residents' activities during flooding. Finally, urban exposure during different flood scenarios was comprehensively simulated and was based on the population and hydrological simulation results, road and building data, and the case study of the Lishui urban district.

The method developed could predict floods as well as the exposure of buildings, roads, and the population at different times and locations. Additionally, it could provide effective reference information for residents' travels and urban disaster management. In summary, this study had four main elements. First, different spatio-temporal distributions of water depth and velocity predictions were obtained using the LISFLOOD-FP model. Second, an ABM was utilized to simulate the spatio-temporal distributions of the population. Third, the impacts of pluvial and fluvial floods on buildings were found to be small, while that on roads and the population was evident. Finally, if residents simply reduced their travels (stayed at home), the exposure of the population in the exposed residential areas increased.

It should be noted that there is no comprehensive way to verify the proposed method. This is because parameters of human behavior and psychological processes are difficult (or, to some extent, impossible) to obtain. In this study, the proposed method was verified indirectly. The actual traffic information for each road intersection was collected and compared with the simulated population results. Additionally, the information for actual water accumulation points was

460 compared with the simulated water accumulation results. However, a few limitations persist. For

461 instance, considerable uncertainties regarding the use and design of the ABM exist. These include

462 differences in the responses of residents of the same type to disasters in the same scenario.

463 Therefore, this study simply attempted to reflect reality. Moreover, simplification of the behavior

464 patterns and disaster responses of residents is inevitable, thus resulting in differences between the

465 simulation results and reality. In addition, the investigation of different durations and intensities

466 of the rainstorm is also relevant. However, the inclusion of other factors was beyond the scope of

467 this research. Therefore, future studies should focus on optimizing the proposed method and

468 incorporating the effects of different durations and intensities of rainstorms.

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

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

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

647   **Figure 4.** A synthetic daily routine generated from the travel survey and census data for an
648   unemployed female agent aged 18–60 years.

649   **Figure 5.** Activity patterns for an unemployed female agent aged 18–60 years during disaster
650   scenarios. (a) Bad weather (weekday) (b) Warning (weekday) (c) Bad weather (weekend) (d)
651   Warning (weekend).

652   **Figure 6.** Number of different block types.

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

654   **Figure 8.** Agent types for daily and disaster scenarios.

655   **Figure 9.** Accumulated water depths and velocities. T means time here.

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

658   **Figure 11.** Population changes in blocks and roads for the six scenarios.

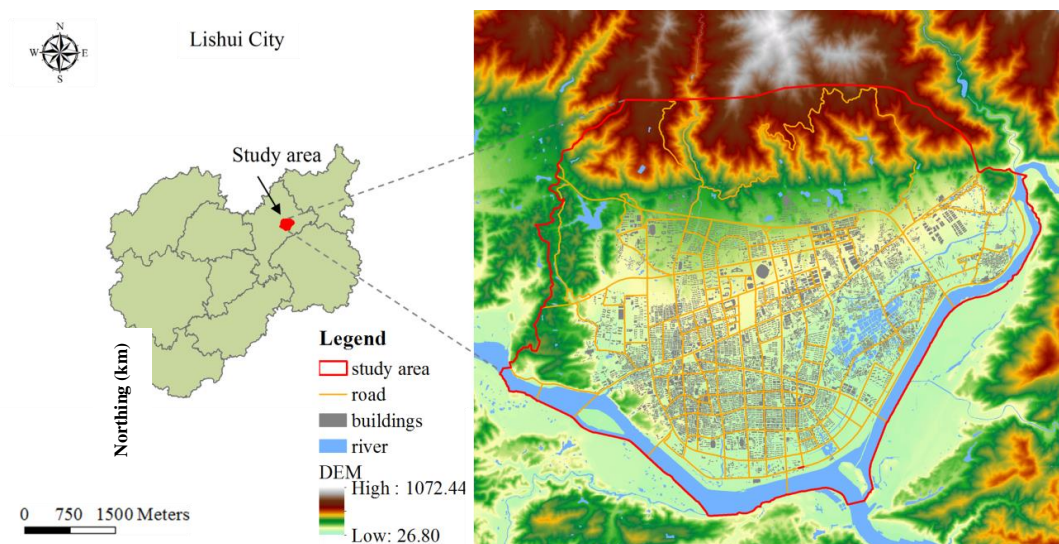
659   **Figure 12.** Population distribution for the six scenarios. T means time here.

660   **Figure 13.** Changes in the population exposure of two blocks for the 12 scenarios. Block 168 was
661   a recreational area, and Block 6 was a residential area.

662   **Figure 14.** Changes in road and building exposures in severely flooded blocks. The exposed road
663   length and building area represent road and building exposures, respectively.

664   **Figure 15.** Map of road and building exposures. T means time here.

665 **Figure 16.** Map of the flooded area indicating the flooding simulation and the real flood in 2014.
666 The information for the flooded area was provided by Lishui City Housing and Urban-Rural
667 Construction Bureau.

668 **Figure 17.** Traffic flow and population simulation results during peak hours on weekdays and
669 weekends. The traffic flow data were provided by the Lishui City Traffic Bureau. Real means
670 measured value here. LQ is Liqing Road, KF is Kaifa Road, HY is Huayuan Road, ZJ is Zijin
671 Road, and LT is Lutang Street.

672

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

675

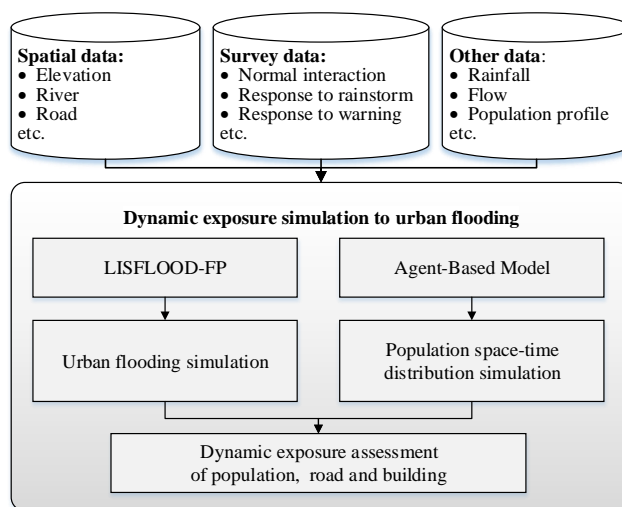



Figure 2. Overview of the dynamic exposure simulation to urban flooding.

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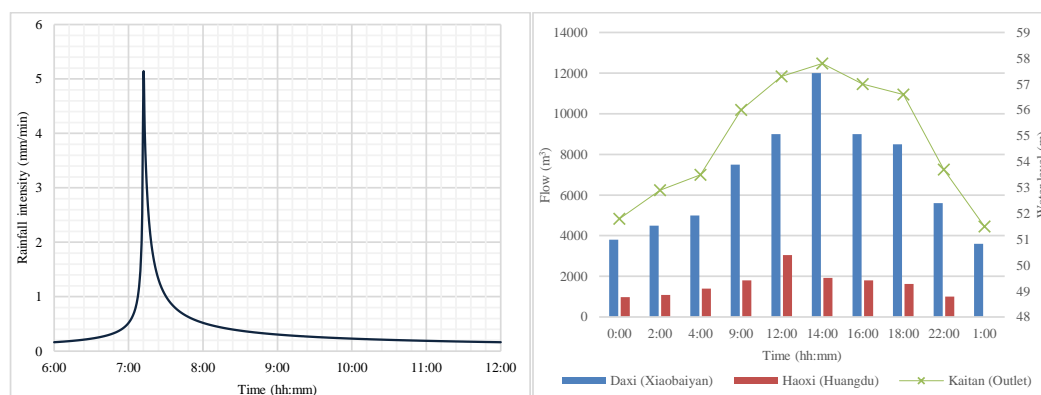
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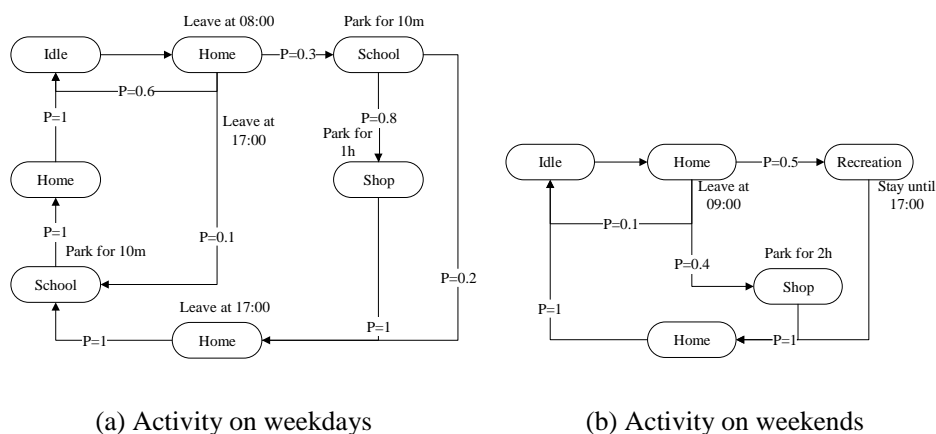
679   (a) Rainfall simulation data   (b) Observational data

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

681   fluvial flood simulation.

682

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

684   **Figure 4.** A synthetic daily routine generated from the travel survey and census data for an
685   unemployed female agent aged 18–60 years.

686

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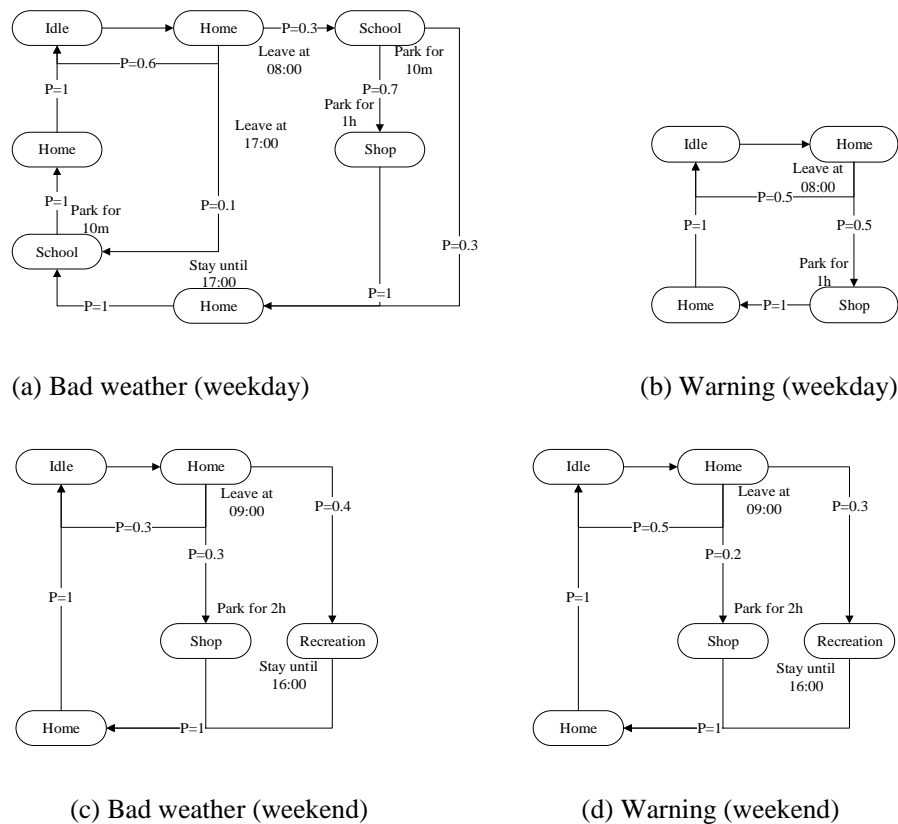
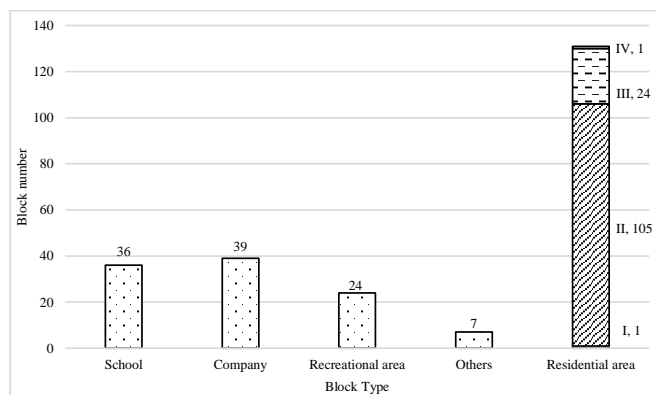
688   (a) Bad weather (weekday)   (b) Warning (weekday)

689

690   (c) Bad weather (weekend)   (d) Warning (weekend)

691   **Figure 5.** Activity patterns for an unemployed female agent aged 18–60 years during disaster
692   scenarios. (a) Bad weather (weekday) (b) Warning (weekday) (c) Bad weather (weekend) (d)
693   Warning (weekend).

694

695

696 **Figure 6.** Number of different block types.

697

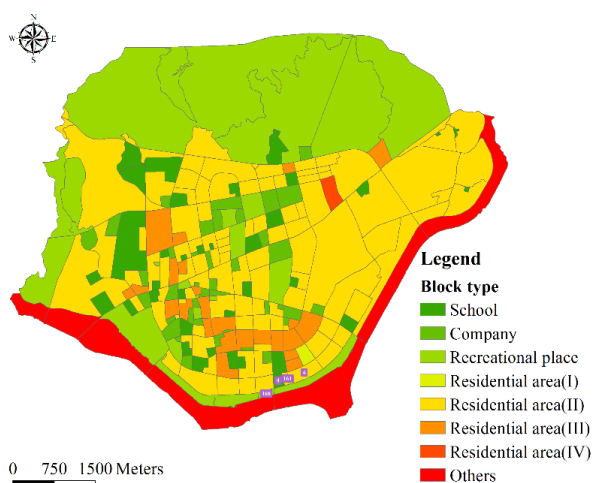
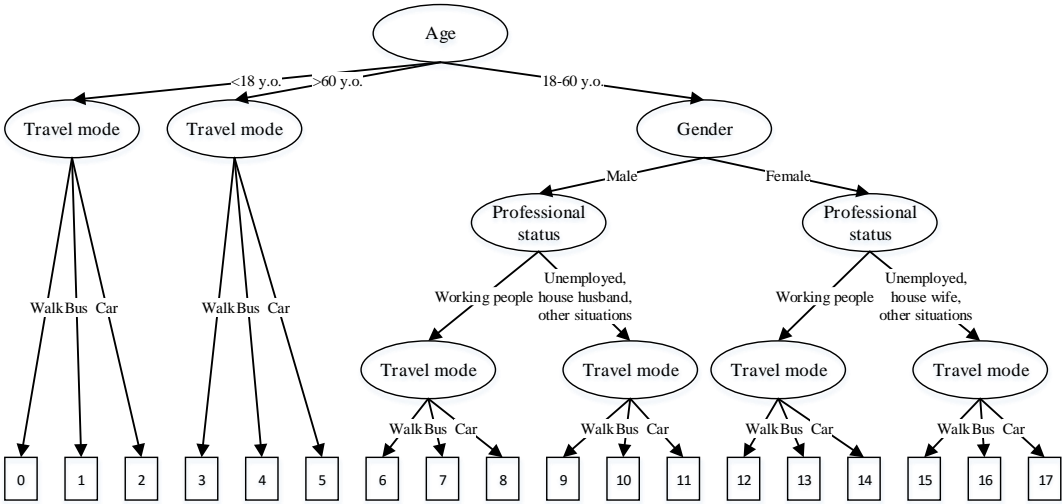
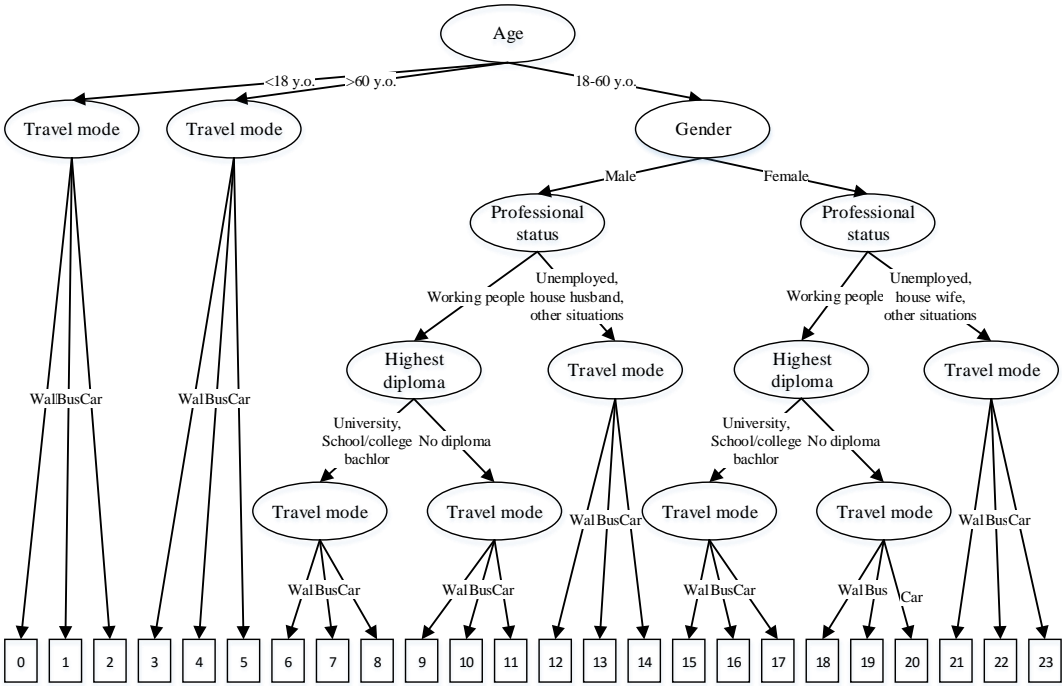



Figure 7. Spatial distribution of blocks.

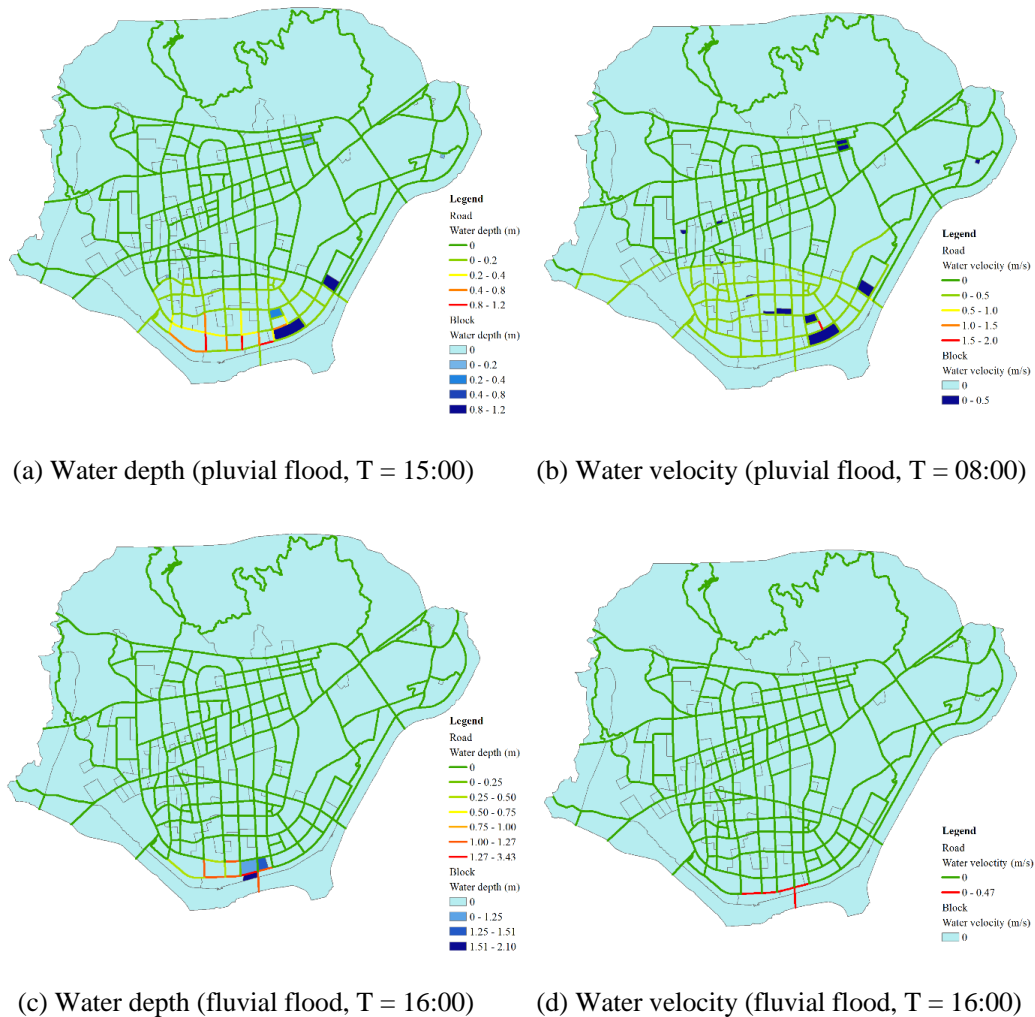
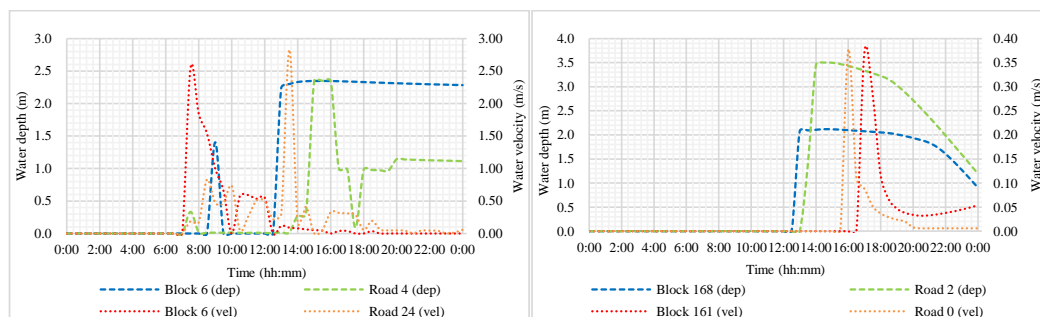
699

700
701
(a) Agent types for daily scenarios

702
703
(b) Agent types for disaster scenarios

704 **Figure 8.** Agent types for daily and disaster scenarios.

705

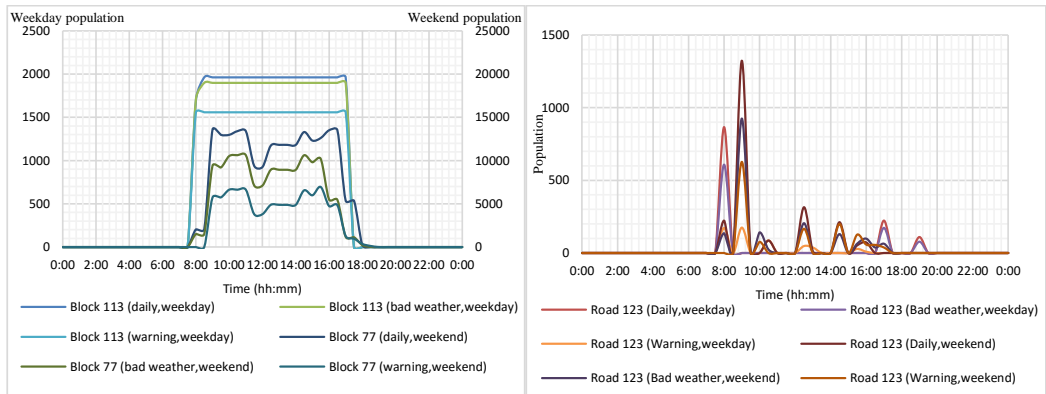
706   (a) Water depth (pluvial flood, T = 15:00)   (b) Water velocity (pluvial flood, T = 08:00)

707

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

709   **Figure 9.** Accumulated water depths and velocities. T means time here.

710

711   (a) Pluvial flood   (b) Fluvial flood

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

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

714

715   (a) Block   (b) Road

716   **Figure 11.** Population changes in blocks and roads for the six scenarios.

717

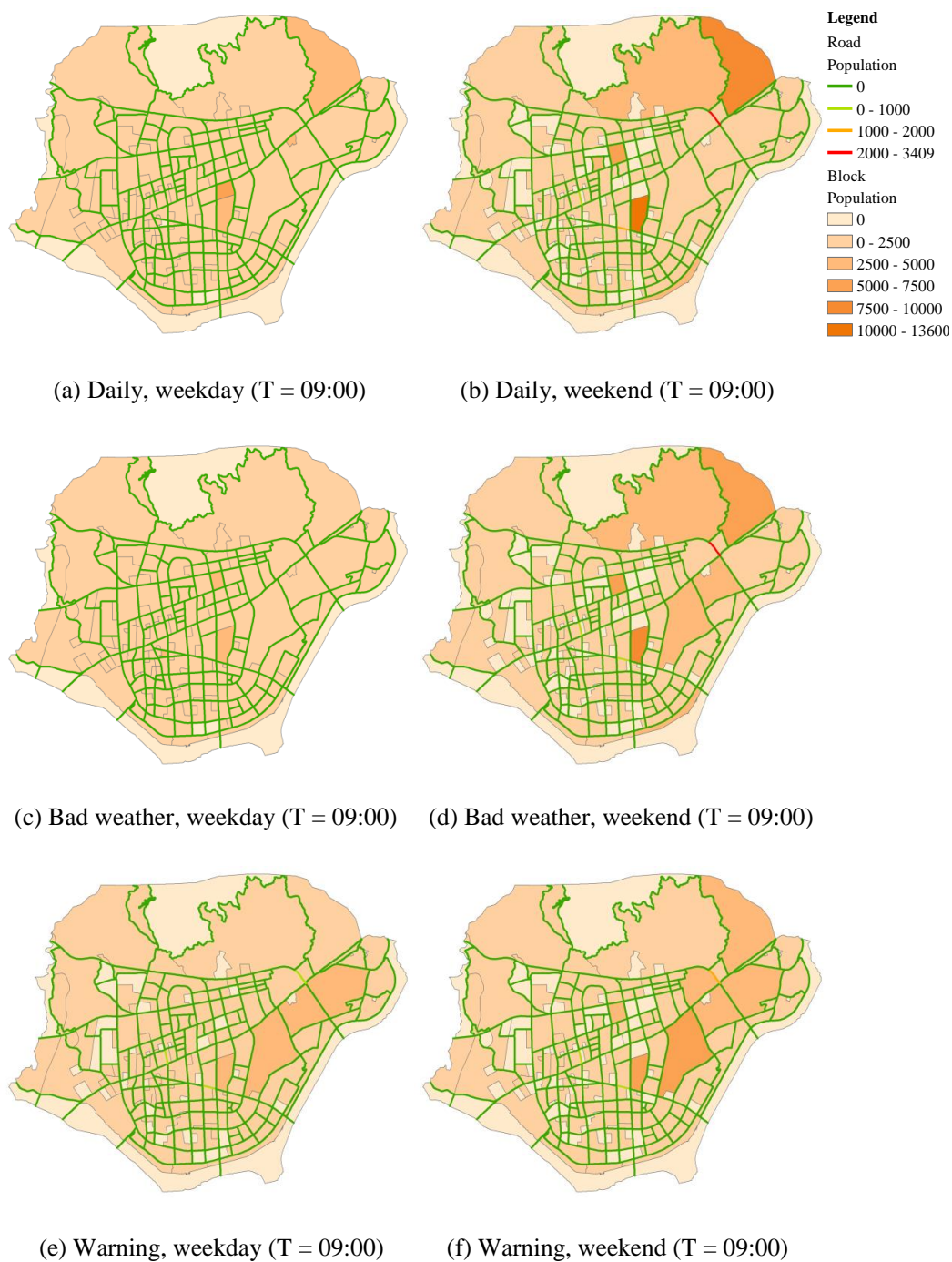
718

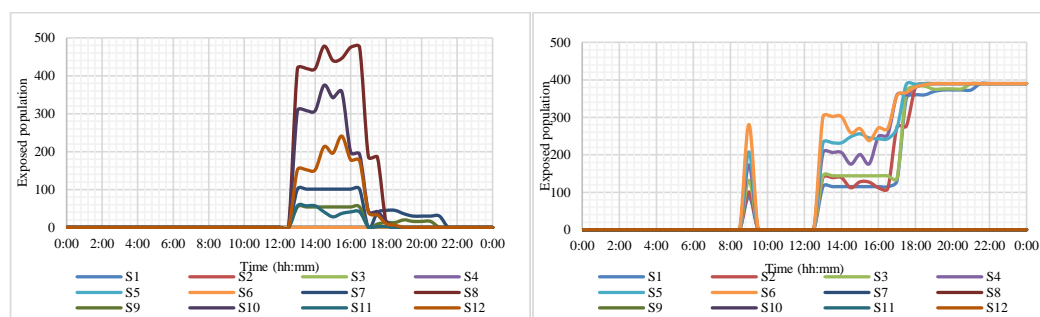
719   (a) Daily, weekday (T = 09:00)   (b) Daily, weekend (T = 09:00)

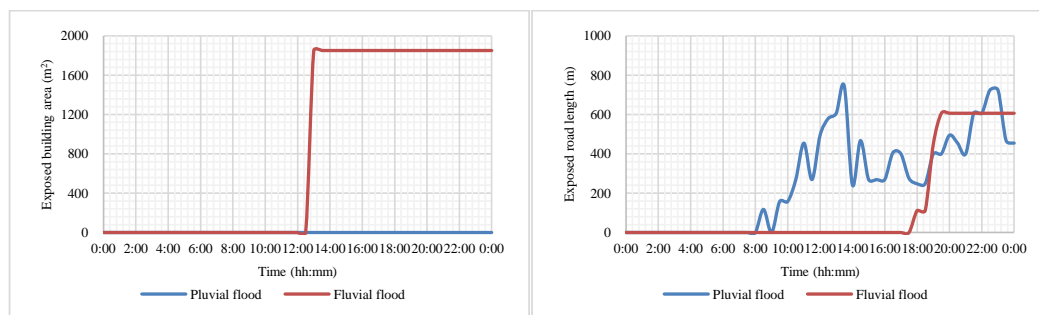
720

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

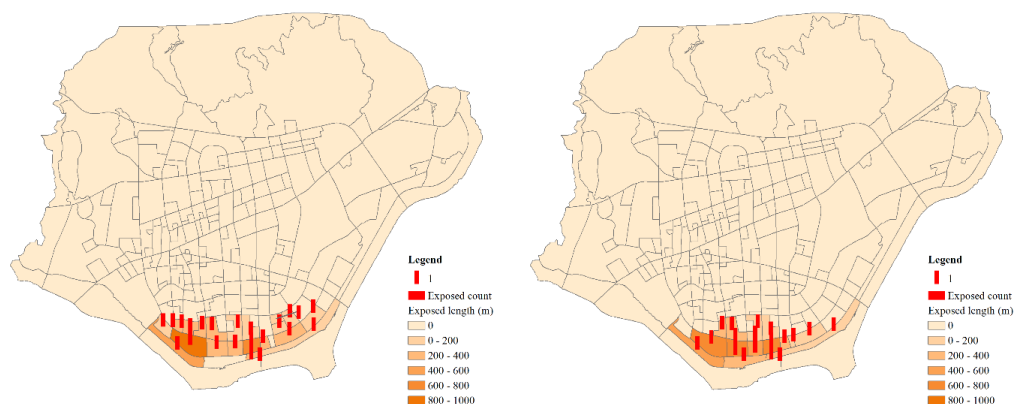
722

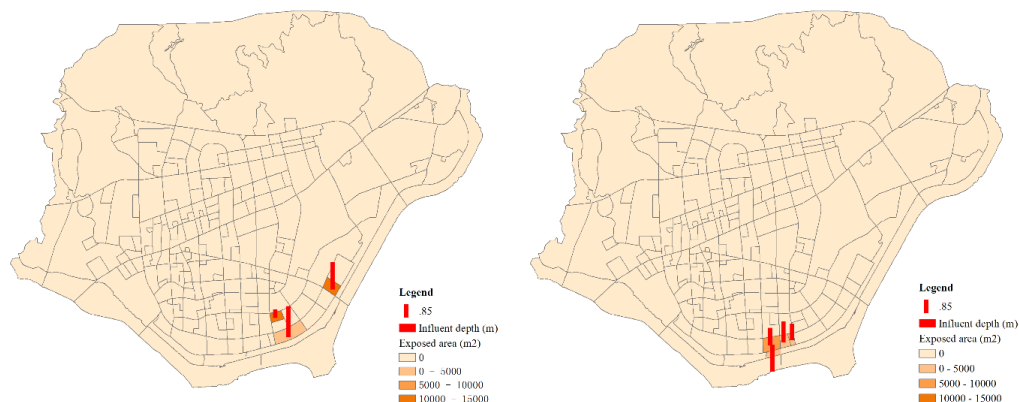
723   (e) Warning, weekday (T = 09:00)   (f) Warning, weekend (T = 09:00)

724   **Figure 12.** Population distribution for the six scenarios. T means time here.

725

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

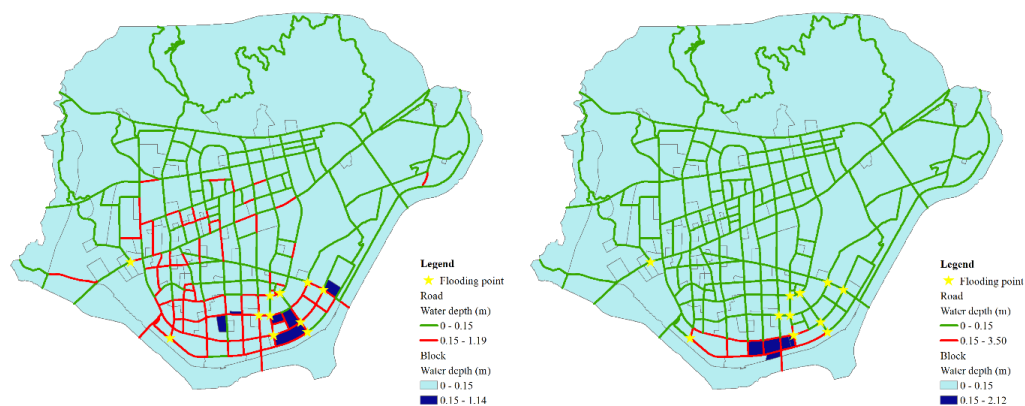
727 **Figure 13.** Changes in the population exposure of two blocks for the 12 scenarios. Block 168
728 was a recreational area, and Block 6 was a residential area.

729

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

731   **Figure 14.** Changes in road and building exposures in severely flooded blocks. The exposed road
732   length and building area represent road and building exposures, respectively.

733

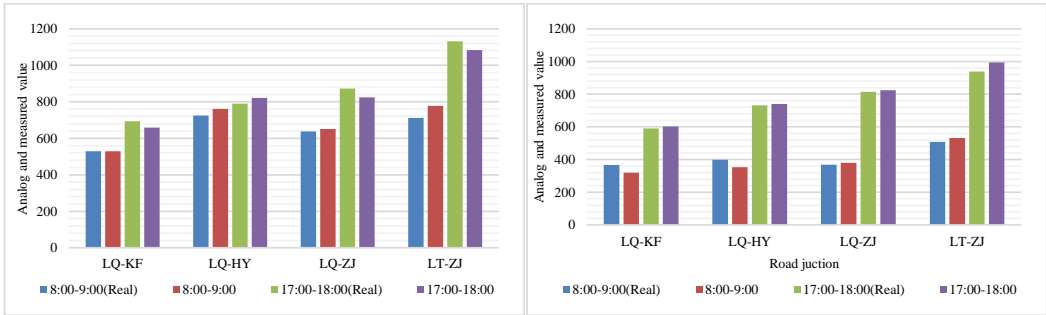
734   (a) Road exposure (pluvial flood, T = 18:30)   (b) Road exposure (fluvial flood, T = 18:30)

735

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

737   **Figure 15.** Map of road and building exposures. T means time here.

738

739   (a) Pluvial flood   (b) Fluvial flood

740   **Figure 16.** Map of the flooded area indicating the flooding simulation and the real flood in 2014.
741   The information for the flooded area was provided by Lishui City Housing and Urban-Rural
742   Construction Bureau.

743

744        (a) Weekday          (b) Weekend

745 **Figure 17.** Traffic flow and population simulation results during peak hours on weekdays and
746 weekends. The traffic flow data were provided by the Lishui City Traffic Bureau. Real means
747 measured value here. LQ is Liqing Road, KF is Kaifa Road, HY is Huayuan Road, ZJ is Zijin
748 Road, and LT is Lutang Street.

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

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

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

752   **Table 4.** Sociodemographic characteristics of the population in the case study area.

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

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

Data	Source	Time	Use
Digital elevation model	Local government	2013	Topography
Basic geographic data	Local government	2015	Location of river, road and building
Hydrological data	Local government	20 Aug 2014	Flow and water level
1km grid population data	National Earth System Science Data Sharing Infrastructure, National Science & Technology Infrastructure of China (http://www.geodata.cn)	2010	Number of residents in grid of the study area.
Population profile	Lishui Statistical Yearbook and Liandu Yearbook (http://tjj.lishui.gov.cn/sjjw/tjnj/201511/t201511 05_448284.htm)	2014	Gender profile, age profile, education level profile, employment profile and travel mode profile were used to classify agent groups.
Traffic flow data	Local government	24 June 2017 to 7 July 2017	The number of vehicles passing through a node within one hour at four intersections from 24 June 2017 to 7 July 2017 in this area,
Water accumulation point	Local government (http://www.zjjs.com.cn/n17/n26/n44/n47/c339 697/content.html)	20 Aug 2014	Location

755

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

Parameter	Value
A	1265.3
b	5.919
c	0.587
n	0.611

757

758   **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

759

760 **Table 4**. Sociodemographic characteristics of the population in the case study area.

Variables	Groups	Percentage (%)
Gender	Male	50.430
	Female	49.570
Age	0-17	18.730
	18-60	63.340
	>60	17.930
Professional status	Employed	55.770
	Unemployed	44.230
Education Level	University, school-college, bachelor	14.457
(Highest diploma)	No diploma	85.543
Travel mode	Walk	25.24
	Bus	43.06
	Car	31.70

761 Note: The data are 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 steps height
1	Residential area I	Garden house, villa	0.35 m(floors>9, 0.60 m)
2	Residential area II	High-rise apartments and new village houses before and after liberation (before 1988); new residential quarters and commercial houses (after 1988)	0.35 m(floors>9, 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(floors>9, 0.60 m)
6	Company	Office building	0.35 m(floors>9, 0.60 m)
7	Recreational area	Public buildings for business, culture, sports and other use	0.35 m(floors>9, 0.60 m)

762