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Evaluating Pluvial Flood Hazard for Highly Urbanised Cities: A Case Study of the Pearl River Delta Region in China

Wei Jian¹, Shanshan Li², Chengguang Lai², Zhaoli Wang², Xiangju Cheng², Edmond Yat-Man Lo^{1,3,4}, Tso-Chien Pan^{1,3,4}

¹Institute of Catastrophe Risk Management, Nanyang Technological University, Singapore

²School of Civil Engineering and Transportation, South China University of Technology, Guangzhou, China

³School of Civil and Environmental Engineering, Nanyang Technological University, Singapore

⁴Green Buildings and Smart Cities Program, Sino-Singapore International Joint Research Institute (SSIJRI), Guangzhou, China

Corresponding author: Edmond Yat-Man Lo (cymlo@ntu.edu.sg)

Abstract. Rapid urbanisation and economic growth in developing Asian countries have exacerbated their exposure to flood hazards, particularly evident in low-lying urban cities that are currently facing increasing risks from extreme precipitations, likely made worse by the impending climate change. We present a set of simplified indices representative of the characteristics of rainfall-runoff process for evaluating pluvial flood hazard using the fuzzy comprehensive evaluation method. The highly urbanised Pearl River Delta (PRD) region in southern China is studied as an example of mapping the regional pluvial flood hazard and assessing the socio-economic exposure at risk. The developed hazard map captures the broad patterns of high flood hazard zones when compared with reported surface water flooding hotspots and the PRD riverine flood map from the 2015 Global Assessment Report. Further analysis on the regional socio-economic profiles suggests that most PRD cities are faced with large flood loss potential, with estimates of approximate 23 million people and 2.4 trillion RMB Gross Domestic Product (GDP) exposed to high flood hazard. Mega cities Guangzhou and Shenzhen top the ranking with over 20% to 40% of their dense urban settlements in the high flood hazard zone. This highlights the impact of human activities on the natural surface runoff process, and the need for robust flood hazard assessment for better understanding and design of holistic solutions towards more adequate flood mitigation systems for continuous urbanisation and future climate conditions.

Keywords: Flood; hazard assessment; urbanisation; Pearl River Delta (PRD); fuzzy comprehensive evaluation.

1. Introduction

Surface water flooding is frequently experienced by large cities worldwide in recent years. It typically occurs after a period of intense downpours exceeding the capacity of the drainage system, leading to disruption of services and economic activities, damage to properties, and even loss of lives. Rapid urbanisation over the past decades has also greatly altered the land use and land cover in urban cities, which together with the immense concentrations of population and wealth, have greatly exacerbated the susceptibility to flood risk. Indeed, the Intergovernmental Panel on Climate Change (IPCC, 2014) has highlighted the increasing risks from extreme precipitations faced by urban areas. As hazard identification is often the first step in disaster risk management, it is important to develop flood hazard maps that can quantify the spatial variation of potential for flooding while also having the robustness to accommodate the change in urban landscape and in precipitation. This in turn provides the basis for better decision making and formulation of relevant policies for flood mitigation and insurance schemes.

The processes that influence surface water flooding in highly urbanised areas are complex and thus difficult to map and manage accurately (Houston et al., 2011). Many factors impact the rainfall-runoff process, ranging from the general terrain profiles and rainfall patterns to small-scale building footprints, local drainage capacity, and even manhole locations. There have been numerous studies on simulating urban flooding using numerical models (e.g. Mark et al., 2004; Mignot et al., 2006; Chen et al., 2012; Chang et al., 2015). These urban storm-inundation models typically couple a 1-D storm sewer model with a 1-D or 2-D surface flow model to depict the rainfall-runoff-inundation process. Recent development of simplified raster-based flood models considers only the 2-D surface flow from direct precipitation with assumptions on rain loss to account for infiltration and drainage (Bates and De Roo, 2000; Yu and Lane, 2006a, b; Sampson et al., 2012; Yu et al., 2016). While these numerical models can provide promising results that are in good agreement with reported flood events, several challenges remain for carrying out flood hazard mapping in highly urbanised areas. Firstly, accurate modelling of the complex drainage systems in urban areas relies on detailed data of drainage networks which is often unavailable or confidential. Secondly, the numerical models tend to be limited to small areas due to large data and computational requirements needed for detailed modelling at high spatial resolution. This means that the changing nature of urban landscapes may not be readily reflected in such flood assessments that may be conducted as a one-off exercise or only updated every few years. Furthermore, as localised modification of land cover often has an impact beyond its immediate surroundings, an alternative assessment tool that can provide regular and adequate evaluation of flood hazard would be highly desirable, which is the objective of the present flood hazard evaluation using the fuzzy comprehensive method.

Fuzzy comprehensive evaluation method is one of the widely used index-based evaluation methods for flood risk assessment in recent years. Fuzzy sets were first introduced by Zadeh (1965, 1978) as a mathematical tool to model subjective uncertainty that results from incomplete knowledge or imprecise data. It has since been widely used in many application areas (e.g. Kruse et al., 1994; Ross, 2010). The fuzzy logic is particularly well suited for disaster risk assessment since the direct cause-effect relationships for the hazard occurrence are not always known. When further combined with geographic information system (GIS) tools, the fuzzy comprehensive evaluation method can be used to analyse spatial patterns based on maps, land survey data, and satellite imagery. Reported studies have used the GIS based fuzzy comprehensive evaluation method to assess various risks, such as seismic liquefaction potential (Xue and Yang, 2014), landslide (Kritikos et al., 2015; Liao et al., 2018), real-time flood forecasting (Nayak et al., 2005; Lohani et al., 2014), and drought prediction (Pongracz et al., 1999; Sun et al.,

2014; Huang et al., 2015). In particular, the fuzzy logic concept has been applied to flood risk evaluation (Jiang et al., 2009; Lai et al., 2015; Hong et al., 2018; Cai et al., 2019). The primary drawback of these studies is that a wide range of indices have been used to collectively represent all components in the risk assessment (i.e. covering hazard, exposure, and vulnerability). This provides less or little distinction on the interactions amongst the components as definitions for exposure and vulnerability may vary for different studies, and it can change independently even for the same case study. In addition, each component influences the potential flood risk differently. As such, the components of flood hazard assessment and risk assessment need to be evaluated independently. Furthermore, the indices used for flood hazard evaluation are commonly derived from a mixture of historical flood records, rainfall patterns, and/or terrain profiles, they can suffer from not capturing the runoff-inundation process adequately which makes it difficult to be generalised for applications in other study areas.

The objective of this study is twofold. Firstly, it is to present and validate a simplified set of indices based on the rainfall-runoff process for evaluating pluvial flood hazard. We build upon the GIS-based fuzzy comprehensive evaluation methodology from Lai et al. (2015) and use seven evaluation indices that capture the meteorological, geological, and hydrological characteristics of highly urbanised areas for flood hazard potential. We further incorporate an empirical treatment in urban areas to account for the influence of urban drainage systems on surface runoff. Secondly, it presents the exposure at risk from pluvial flooding through maps reflecting the regional socio-economic exposures. The Pearl River Delta (PRD) region in China with its nine cities has been selected as the case study due to its massive urban concentration of population, economic assets, and infrastructure along with its exposure to high flood hazards (Hallegatte et al., 2013). We compare the developed pluvial flood hazard map at a spatial resolution of $1 \text{ km} \times 1 \text{ km}$ with reported surface water flooding hotspots from the literature and the riverine flood hazard map of the region from the 2015 Global Assessment Report. The developed map is able to capture the characteristics of surface water flooding and the increased flooding potential adjacent to major rivers. This demonstrates the adequacy of the proposed indices and methodology. The generated regional flood hazard map is further analysed alongside datasets for the population and Gross Domestic Product (GDP) to identify the exposures at risk at the individual city level for the PRD region.

The remainder of the paper is organised as follows. Section 2 introduces the case study area. The detailed methodology for flood hazard assessment and datasets used are described in Section 3. Section 4 presents the developed pluvial flood hazard map and the exposed population and GDP. Final conclusions are summarised in Section 5.

2. PRD case study region

The PRD region, located in the Guangdong province in southern China, encompasses a total area of 54,764.16 km^2 within $21^\circ\text{--}25^\circ\text{N}$ and $111^\circ\text{--}116^\circ\text{E}$ (Fig. 1) (Guangdong Bureau of Statistics, 2018). Like many other Asian cities, the PRD region has undergone rapid development over the last few decades, with the population rising from 23.7 million in 1990 to 61.5 million in 2017 (Guangdong Bureau of Statistics, 2018). It consists of nine cities, six of which are ranked in the top 200 most competitive metropolitan areas worldwide in 2017 with Shenzhen and Guangzhou in the 6th and 15th place, respectively (Ni et al., 2018). Flooding in the PRD region has been a long-standing natural hazard for centuries due to its geographical location. Situated at the deltaic plain downstream of the Pearl River basin, it has three major rivers (the West, North, and East Rivers) that meander

108 across the region (Fig. 1). They are further interconnected by a complex network of crisscrossing tributaries before
discharging to the South China Sea via eight outlets. Together with its long coastline, the region is naturally
110 vulnerable to hydrological and tropical cyclone events. In response, extensive flood protection measures have
been built along the riverbanks and coastline over the last two decades. While these measures are effective in
112 protecting the cities from major riverine or coastal flood events, surface water flooding from intense rainfall in
these cities has become more frequent in recent years due to urbanisation and ageing drainage systems. According
114 to the data from the Guangdong government, approximately 10%-15% of the population on average were affected
by flood loss events every year between 2000 and 2015 in Guangdong province (Editorial Committee of Disaster
116 Prevention and Mitigation Yearbook of Guangdong Province, 2013, 2015). The average annual direct economic
loss from these flood events is approximately 0.5% of the provincial GDP, a rather significant number given the
118 rapid rise in the regional GDP over the recent decades.

3. Materials and methods

120 3.1 Fuzzy comprehensive evaluation method for flood hazard assessment

The fuzzy comprehensive evaluation method is an evaluation process based on fuzzy logic. It uses membership
122 functions to describe the degree of membership of the discrete input data. Variables may have a continuous value
under each membership class from 0 (no membership) to 1 (full membership), thus allowing an object to be
124 categorised into more than one exclusive set with varying degrees of truth (Dubois and Prade, 2015). We have
generally followed Lai et al. (2015) which detailed the procedures for carrying out the fuzzy comprehensive
126 evaluation with the main steps summarised below. For this study, the PRD region was discretised into grids of
size 1 km × 1 km with each grid being assigned attribute variables used for determining the evaluation indices.
128 The total number of grids is 51,304 excluding waterbodies and small offshore islands.

The fuzzy comprehensive evaluation starts by selecting a set of independent evaluation indices as the key
130 determinants for the objective of the evaluation—flood hazard in this study. Thus, these indices need to best
represent the main contributing factors to flood hazard. This index set is represented by a vector, $\mathbf{U} =$
132 $[u_1, u_2, \dots, u_m]$, for a total number of m indices. Next, an index-specific grading standard matrix $\mathbf{V}$ is applied to
the index vector $\mathbf{U}$ which describes the threshold values for different memberships for each index. It is represented
134 as

$$\mathbf{V} = \begin{bmatrix} v_{1,1} & \dots & v_{1,n} \\ \vdots & \ddots & \vdots \\ v_{m,1} & \dots & v_{m,n} \end{bmatrix}, \quad (1)$$

where n is the number of memberships for evaluation.

136 Given the index vector $\mathbf{U}$ and the grading standard matrix $\mathbf{V}$, a fuzzy evaluation matrix $\mathbf{R}$ can be established
to describe the membership degrees of each grid as

$$\mathbf{R} = \begin{bmatrix} r_{1,1} & \dots & r_{1,n} \\ \vdots & \ddots & \vdots \\ r_{m,1} & \dots & r_{m,n} \end{bmatrix}, \quad \text{where } r_{i,j} = f(\mathbf{U}, \mathbf{V}). \quad (2)$$

138 The matrix elements ($r_{i,j}$) describe the membership degrees of the grid and are given by the membership function
 140 as, $f(\mathbf{U}, \mathbf{V})$ which computes the distribution of memberships. A piecewise linear membership function is used herein

$$r_{i,j} = \begin{cases} 0 & u_i \leq v_{i,j-1} \text{ or } u_i \geq v_{i,j+1} \\ \frac{u_i - v_{i,j-1}}{v_{i,j} - v_{i,j-1}} & v_{i,j-1} < u_i < v_{i,j} \\ \frac{v_{i,j+1} - u_i}{v_{i,j+1} - v_{i,j}} & v_{i,j} < u_i < v_{i,j+1} \end{cases} \quad \text{for } j \neq 1 \text{ or } j \neq n$$

$$r_{i,j=1} = \begin{cases} 1 & u_i \leq v_{i,j} \\ \frac{v_{i,j+1} - u_i}{v_{i,j+1} - v_{i,j}} & v_{i,j} < u_i < v_{i,j+1} \\ 0 & u_i \geq v_{i,j+1} \end{cases} \quad (3)$$

$$r_{i,j=n} = \begin{cases} 0 & u_i \leq v_{i,n-1} \\ \frac{u_i - v_{i,n-1}}{v_{i,n} - v_{i,n-1}} & v_{i,n-1} < u_i < v_{i,n} \\ 1 & u_i \geq v_{i,n} \end{cases}$$

where u_i is the value of index i and $v_{i,j}$ is the threshold value for membership j of the index.

142 The evaluation indices are likely to have differing degrees of influence on the objective of evaluation, a weight
 set, $\mathbf{w} = [w_1, w_2, \dots, w_m]$, is thus assigned to the indices to reflect their relative importance, with the weight vector
 144 satisfying

$$\sum_{i=1}^m w_i = 1 \quad , \quad w_i \geq 0 . \quad (4)$$

The final membership set $\mathbf{C}$ is calculated by combining the weight vector $\mathbf{w}$ and the matrix $\mathbf{R}$ so that the
 146 evaluation matrix can be converted into a best estimate,

$$\mathbf{C} = \mathbf{w} \times \mathbf{R} = [w_1, w_2, \dots, w_m] \times \begin{bmatrix} r_{1,1} & \cdots & r_{1,n} \\ \vdots & \ddots & \vdots \\ r_{m,1} & \cdots & r_{m,n} \end{bmatrix} = [c_1, c_2, \dots, c_n] . \quad (5)$$

When used for flood hazard evaluation, the final membership vector represents the range of hazard levels at each
 148 grid. The largest value represents the most likely hazard membership (c_f) at the grid under consideration based on
 the maximum membership degree law, i.e.

$$c_f = \max(C_k: k = 1, \dots, n) . \quad (6)$$

150 3.1.1 Determine the weight vector, $\mathbf{w}$

There have been a number of approaches to determine the weight vector using multi-criteria decision-making
 152 methods in the literature. They are generally classified into objective or subjective methods. The objective
 approach determines the weights of criteria based on the usefulness of information in a decision matrix through

mathematical models, whereas subjective methods rely on the judgements and opinions of the decision makers. These two approaches can be further integrated to form a more balanced model for decision making.

In Lai et al. (2015), the well-known Analytic Hierarchy Process (AHP) (Saaty, 1980) and the entropy method (Hwang and Yoon, 1981) were used to calculate the subjective and objective weights, respectively. The AHP method is based on human judgements using pairwise comparisons to determine the preferences or hierarchy of indices following the Saaty scale of importance. The matrix constructed following the pairwise comparison is then used to calculate the weighting based the principal eigenvector method (Saaty, 1977). The AHP method has the advantage of using a simple mathematical model to transform qualitative judgements of decision makers into a priority vector for the evaluation indices. However, it is purely based on expert opinions and does not take into consideration the degree of differentiation in the index values. It is possible that an index with a high AHP weight has very small amount of useful information (measured as entropy) in its values that cannot support a good differentiation and thus, could potentially lead to unsatisfactory evaluation results. This subjective weight can be complemented by the entropy weight method which evaluates weights based on the degree of dispersion in the index values. The entropy method is based on Shannon's entropy theory (Shannon, 1948) which measures the usefulness of information in datasets. The information entropy formulae assign a higher weight for dataset that has a larger information entropy. The objective entropy weight allows us to understand the relative weights of the indices that are supported by the nature of the index values.

Given the relative merits of the AHP and entropy weights, we can further integrate the two weights to obtain an optimised weight that takes into account both the human judgements and nature of index values. We follow Lai et al. (2015) to calculate the combined weight using the game theory approach which models the two weights as two cooperative players. This is more desirable than the simple arithmetic mean of the subjective and objective weights as our aim is to retain the relative importance among the indices from expert opinions while ensuring that there is no conflict from the index values. The game theory approach can resolve this by minimising the deviation between the optimal combined weight and input weight vectors. This is achieved by solving the following

$$\sum_{j=1}^n \alpha_j \cdot \mathbf{w}_k \cdot \mathbf{w}_j^T - \mathbf{w}_k \cdot \mathbf{w}_k^T = 0 \quad (k = 1, 2, \dots, n) \quad (7)$$

where $\mathbf{w}$ is the input weight vector set and α_j is the weight coefficient. The final combined weight would be the solution that reaches the Nash Equilibrium (Nash, 1950), which takes the following form

$$\mathbf{w}^* = \sum_{k=1}^n \alpha_k \cdot \mathbf{w}_k \quad (8)$$

where $\mathbf{w}^*$ is the optimised weight vector and α_k is the optimal weight coefficient. Readers are referred to Lai et al. (2015) for more details on the step-by-step formulae.

3.2 Evaluation index selection and data processing

Historically, major flood events in the PRD region are generally caused by three main factors: (i) high water levels in the major river network entering the PRD region (known as riverine flooding); (ii) intense precipitation within the PRD (pluvial flooding); and (iii) high astronomical tides/storm surges along the coastline (coastal flooding). We examined the flood loss events of recent years as reported in the Guangdong Disaster Prevention and

Mitigation Yearbooks (2000-2015) and found that direct precipitation in the PRD region is the top cause for most
 188 damaging flood events over the recent decades (Editorial Committee of Disaster Prevention and Mitigation
 Yearbook of Guangdong Province, 2013, 2015). We have therefore focused on this mechanism for our selection
 190 of evaluation indices for flood hazard assessment.

In Lai et al. (2015) work, ten indices were used to assess the flood risk which consists of seven indices on
 192 hazard: maximum 3-day precipitation, typhoon frequency, runoff depth, elevation, distance to the main road,
 distance to the river, and slope; and three indices on vulnerability: population density, GDP density, and cultivated
 194 acreage proportion. They define the exposure (e.g. population and GDP) as part of vulnerability and consider the
 interaction of hazard and vulnerability for flood risk evaluation. In this study, however, our focus is on flood
 196 hazard evaluation. We make the distinction between the hazard and exposure components of risk assessment as
 we consider their interdependence to be relatively weak, i.e. occurrence of flooding at a particular site is largely
 198 independent to the local level of exposure. Furthermore, the indirect influence from human activities to flooding
 potential is implicitly captured by land use and land cover data as affecting runoff and infiltration. Thus, we
 200 simplified the indices from Lai et al. (2015) to include only those that directly represent the meteorological,
 geological, and hydrological characteristics of the intense precipitation patterns and surface flow routing process
 202 typically found in the PRD region. We use the following seven indices for flood hazard assessment: maximum 1-
 day precipitation, number of heavy precipitation days, elevation, slope, distance to waterbody, soil type, and
 204 runoff coefficient. Table 1 summarises the definition and data sources of these indices.

Five membership degrees are used to categorise the index values, which implies that the final flood hazard
 206 evaluation set C also has five levels, termed as low hazard, relatively low hazard, moderate hazard, relatively high
 hazard, and high hazard. These hazard levels describe the flooding potential of an area in terms of likelihood of
 208 flooding, based on the evaluation of membership degrees of each individual index values and the relative
 importance of the seven indices. A high hazard level means that the area has a higher chance of experiencing
 210 frequent and/or severe inundation than others within the study area based on its local long-term rainfall pattern
 and land characteristics. As the membership classification is based on differentiating the index values, the final
 212 hazard levels represent a qualitative ranking of the relative flood potential within the study area.

Thus, we use seven indices and five memberships, i.e. $m = 7$ and $n = 5$ in Eqn (1), in our flood hazard
 214 evaluation. All seven index layers are converted into raster format of grid size $1 \text{ km} \times 1 \text{ km}$, with re-gridding
 performed as needed for evaluation in GIS. They are further graded into five memberships for the computation of
 216 fuzzy evaluation matrix R . The needed data processing and grading standards for the seven indices are described
 in detail below.

Table 1. Definition of the evaluation indices and the datasets used in this study.

	Index	Description	Definition	Unit	Resolution	Data source
Meteorological Characteristics	M1DP	Maximum 1-day precipitation	Long-term average of the annual maximum 1-day precipitation	mm	Individual weather stations	Annual maximum daily precipitation data from the Hydrological Bureau of Guangdong Province (http://swj.gd.gov.cn/)
	AHPD	Number of heavy precipitation days	Long-term average annual count of days with 1-day precipitation exceeding 50 mm	day	0.5° lat./lon.	Gridded daily precipitation datasets (1961-2013) from China Meteorological Administration (http://cdc.nmic.cn/home.do)
Geological Characteristics	EL	Elevation	Elevation from the mean sea level	m	1 arc-second	NASA Shuttle Radar Topography Mission (SRTM) Version 3.0 Global 1 arc second (https://www2.jpl.nasa.gov/srtm/)
	SL	Slope	Slope of the terrain	degree	1 arc-second	As above for EL
	DtW	Distance to waterbody	Distance to major rivers and lakes	m	1 arc-second	As above for EL
Hydrological Characteristics	ST	Soil type	The Harmonized World Soil Database	-	1 km	Food and Agriculture Organization of the United Nations (http://www.fao.org/home/en/)
	RC	Runoff coefficient	Runoff coefficient based on the land use and land cover type and drainage pipeline density for urban land cover	-	1 km	Land use and land cover map (2015) from the Resources and Environment Science Data Center of the Chinese Academy of Sciences (http://www.resdc.cn/Default.aspx)

3.2.1 Indices on meteorological characteristics

The Guangdong province has a long-term annual mean precipitation ranging between 1600 and 2600 mm, 85% of which occurs during the wet season spanning from April to September. Storms typically come in the forms of monsoon in the early wet season (April to June) and tropical cyclones in the late wet season (July to September). We have selected two indices to quantify the meteorological influence on the flood hazard: the maximum 1-day precipitation (M1DP) and average number of heavy precipitation days per year (AHPD). Given the strong influence of tropical cyclone systems and high urbanisation in the PRD region, the 1-day duration is representative of the rainfall intensities that could lead to flood loss events. Together with AHPD, they are able to reflect the characteristics of heavy rainfall events in the PRD region in terms of their peak intensities and annual frequencies.

The M1DP is calculated from the annual maximum 1-day precipitation data from 154 weather stations in the PRD region as shown in Fig. 2. The lengths of the recorded data range from 35 to 100 years, binned in the figure as ≥ 50 years or < 50 years. The average maximum 1-day precipitation was calculated for the respective weather stations before distributing onto the $1 \text{ km} \times 1 \text{ km}$ grids using the Kriging method. Fig. 3(a) shows that the spatial distribution of M1DP index values with rainfall intensities exhibits a gradual increase from the mountainous northwest region to the coastal region in the southeast. The west side of the Pearl River Estuary (e.g., Jiangmen, Zhuhai) tends to have higher 1-day precipitation than the east side, this is likely to be caused by the heavy downpours from tropical cyclones that are more likely to make landfall near or to the west of the Pearl River Estuary.

The heavy precipitation days used in AHPD are defined as days with 24-h total precipitation exceeding 50 mm. This follows the China Meteorological Administration (CMA)'s definition of torrential rainfall as 24-h precipitation exceeding 50 mm. A different dataset, gridded (0.5°) daily precipitation dataset provided by the CMA, was used for deriving the AHPD. The dataset is reanalysed from observations over national rain gauge stations in the region, and thus capable of capturing the rainfall variability (Wang et al., 2017). The dataset is available for years between 1961 and 2013 with its spatial coverage shown in 0.5° grids in Fig. 2. A spatial pattern similar to that of the M1DP can be observed for the AHPD (Fig. 3(b)).

We used different grading standards for the two meteorological index layers to ensure that the rainfall variations are reflected at both regional (PRD) and city levels. In order to preserve the spatial variability of M1DP, we have chosen to classify the index layer into five memberships using the respective return-period based 1-day precipitation intensities at city level. Five return periods of 5, 10, 20, 50, and 100 years were selected as the threshold values for the five memberships. Fig. 4 presents the graded memberships of M1DP index values for the nine cities in the PRD. Conversely, the AHPD layer is graded into five memberships at the regional level using the Jenks natural breaks classification method in the ArcGIS toolset (see Table 2). The Jenks classification is based on natural groupings inherent in datasets that aims to maximise the differences between the groupings. The classification was performed at the regional level to reflect the regional variation of rainfall characteristics that is absent from the M1DP index layer after its grading at city level. Thus, together with the city level M1DP, rainfall variations at both regional and city level are retained from the original rainfall datasets.

Table 2. Grading standards used for AHPD, DtW, ST, and RC in this study.

Index	Level 1	Level 2	Level 3	Level 4	Level 5
AHPD (days)	3	4	5	6	7
DtW (m)	52562	38000	24640	16340	7100
ST	Loamy sand or Sand	Sandy loam	Clay loam	Silty clay	Clay
RC	0.18	0.35	0.50	0.65	0.75

3.2.2 Indices on geological and hydrological characteristics

The potential of flood damage from heavy rainfall events are dependent on the characteristics of the natural and built environment of the area. Considering the key hydrological processes during an urban storm event covering infiltration, drainage, and surface runoff, we have selected five indices to represent: (i) the conveyance and detention of storm water (indices of elevation and terrain slope); (ii) natural and man-made capacity to infiltrate and reduce surface runoffs (indices of soil type and runoff coefficient); and (iii) the proximity to water bodies (index of distance to major river networks and lakes). Figure 5 shows the spatial distributions of these five indices in the PRD region.

The runoff coefficient (RC) describes the relationship between received precipitation and surface runoff. Table 3 lists the recommended RC values for various land use and land cover types (Lai et al., 2016). Urban areas are typically modelled as having a higher surface RC value owing to their impervious land cover. However, a major source of runoff loss in developed areas is the in-built drainage systems that can drain storm water by gravity or even via pumps. Thus, the constant RC value for urban land cover needs to be adjusted according to this additional drainage and storage capacity in highly urbanised areas. Zhang et al. (2015) shows that there is a strong correlation between the number of surface water flooding hotspots and the density of rainwater pipelines in the nine sub-basins of Shenzhen. Given the availability of such drainage pipeline density data for the PRD cities (China Urban Construction Statistical Yearbook 2016 (MOHURD, 2018)), we modify the RC value for urban land type using the pipeline density data (see Table 4). The lower and upper RC thresholds of 0.60 and 0.85, respectively, are set following the range of RC values (0.60-0.85) recommended for urban areas in the Code for Urban Wastewater and Stormwater Engineering Planning GB 50318-2017 (MOHURD, 2017). A linear relationship is then assumed between the drainage pipeline density and the RC value, with the city of the highest pipeline density (Foshan) having a modified RC of 0.65 and the maximum RC value of 0.85 for a city with no pipelines. Table 4 lists the modified RC values used for the urban areas in the nine cities. It is evident from Fig. 5(a), (c) and (e) that the major urban settlements (typically associated with high RC values) are concentrated in the low-lying flood plains along the major river networks and coastal zones.

Similar to the meteorological indices, indices that represent the terrain characteristics (elevation and slope) are graded using the Jenks natural breaks classification method at the city level. This highlights the topographic depressions where excess surface runoff may form ponding at the local scale. The other three indices are

categorised at the regional level by either Jenks natural breaks or manual method according to the thresholds listed in Table 2.

Table 3. Land use land cover types and their corresponding runoff coefficient (RC) used in this study.

Land use/cover types	RC	Land use/cover types	RC
Cropland	0.6	Water	1.0
Forest	0.15	Urban	0.85
Shrub	0.18	Rural settlement	0.45
Sparse vegetation	0.45	Sandy	0.6
Grass	0.3	Wetland	0.5
Bare land	0.7	Others	0.7

Table 4. Modified runoff coefficients for urban areas (as indicated by the land cover map) for the nine PRD cities.

City	Drainage pipeline density in built area (km/sq. km, 2016)	Modified RC for urban land type
Guangzhou	9.70	0.756
Shenzhen	14.63	0.685
Zhuhai	17.62	0.651
Foshan	17.73	0.650
Huizhou	9.11	0.747
Dongguan	9.80	0.739
Zhongshan	8.00	0.760
Jiangmen	11.70	0.718
Zhaoqing	7.49	0.765

3.2.3 Assigning weights to the indices

For the AHP analysis, we invited eight faculty members from Department of Hydraulic Engineering, South China University of Technology, who have extensive experience on flood modelling and assessment in the PRD region to score the seven indices in a two-step pairwise comparison table as that shown in Table 5. The two main categories—meteorological and land characteristics—were compared for their relative importance in Step 1 before the pairwise comparison among the individual indices under each category were conducted separately in Step 2a and 2b. The received responses were tested for their consistency using the consistency ratio (Cr) to ensure

that $Cr < 0.1$, i.e. consistent judgement. We then used the principal eigenvector method by Saaty (1977) to calculate the priority weight based on the geometric mean matrix from the collected pairwise comparison responses with results shown in Table 5. The final subjective weight (SW) is calculated by multiplying the index priority weights in Step 2a and 2b with the priority weights of their respective category from Step 1. The final SW is shown in Table 6.

Table 5. The two-step pairwise comparison matrix and the calculated priority weight for AHP analysis. Values shown are the calculated geometric means from the collected expert opinions.

<i>Step 1: Main Categories</i>	Meteorological factors		Land characteristics factors			Priority Weight
Meteorological factors	1		0.667			0.400
Land characteristics factors	1.5		1			0.600
<i>Step 2a: Meteorological Factors</i>	M1DP		AHPD			Priority Weight
M1DP	1		1.25			0.556
AHPD	0.8		1			0.444
<i>Step 2b: Land Characteristics Factors</i>	EL	SL	DtW	ST	RC	Priority Weight
EL	1	1.0	1.0	1.0	0.5	0.158
SL	1.0	1	1.0	1.0	0.333	0.144
DtW	1.0	1.0	1	1.0	0.333	0.144
ST	1.0	1.0	1.0	1	0.286	0.140
RC	2.0	3.0	3.0	3.5	1	0.413

The objective weight (OW) by the entropy method was carried out using the raster calculator in ArcGIS. We have further integrated the SW and OW weights using game theory, results are shown in Table 6. The SW suggests that the M1DP, RC, and AHPD are the three most important indices for PRD flood hazard evaluation. This generally agrees with the OW which also shows these three indices in its top 3 in ranking, although the relative importance of M1DP and AHPD is opposite to that of SW. Furthermore, the SW shows a slight bipolar division with M1DP, AHPD, and RC being of higher importance than EL, SL, DtW, and ST, whereas the differences in the OW for these indices are more gradual. Thus, the optimised combined weight from minimising the deviations from the SW and OW was driven by the characteristics of SW with minor adjustment from the influence of OW. The optimal weight coefficient, α_k , from Eqn. (8) was {0.93, 0.07} for SW and OW, which means that the relative differentiation in the index values is able to maintain the subjective rankings obtained from human judgement.

Thus, the combined weight was used as the weight vector ($\mathbf{w}$) for construction of the final membership set $\mathbf{C}$ in Eqn (5).

Table 6. Subjective, objective, and combined weights for the seven indices in this study.

Indices	Subjective Weight	Objective Weight	Combined Weight
M1DP	0.222	0.120	0.215
AHPD	0.178	0.183	0.178
EL	0.095	0.080	0.094
SL	0.087	0.103	0.088
DtW	0.087	0.141	0.090
ST	0.084	0.143	0.088
RC	0.248	0.228	0.246

3.3 Processing the Global Assessment Report (GAR15) flood maps for validation

As part of the validation for our flood hazard map, we processed the riverine flood maps of the PRD region as reported in the Global Assessment Report on disaster risk reduction. The global assessment was conducted by the United Nations International Strategy for Disaster Reduction (UNISDR), the most recently updated report is in 2015 (termed GAR15 hereafter) (CIMA Foundation, 2015; UNISDR, 2015). It is noted here that the PRD region has extensive protection measures for riverine flooding hazard, generally comprising of upstream reservoirs for controlling the river stage into the PRD region and extensive levee systems for major townships. As such flood risk caused by large stream flows originating from upstream of the Pearl River Basin is greatly mitigated; however, intense rainfall conditions within the PRD coupled with high river stage may still lead to localized fluvial flooding during the wet season. Hence, our derived flood hazard map should also be able to reflect the potential of riverine flooding for areas adjacent to the major rivers from intense rainfall conditions under high river stage.

The GAR15 flood assessment was conducted using the streamflow and topographic data for major river basins, where a simplified approach based on Manning's equation was employed for modelling the water levels downstream based on river discharge quantiles introduced at major river sections. Some level of flood defences is assumed for places with high exposure. We generate a long-term expected riverine flood hazard map by calculating an annual average flood depth (AAFD) using the return-period based GAR 15 flood hazard maps. This AAFD representing an annualised flood depth of all potential events in a year is calculated as

$$AAFD = \sum_i p_i h_i \quad (9)$$

where p_i is the probability of occurrence of the event (i) and h_i is the flood depth of the event. The probabilistic hazard maps with return periods of 25, 50, 100, 200, 500 and 1000 years were used for the AAFD calculation.

This AAFD map is used for comparison with the developed flood hazard map in section 4.1.2.

4. Results and discussion

4.1 Flood hazard map result and validation

The developed pluvial flood hazard map for the PRD region is shown in Fig. 6. The general pattern is characterised by higher hazard levels in the downstream floodplains of major river networks and the southwestern coastal region. This is largely due to more intense rainfall conditions, milder terrain, and more impervious built-up areas in these areas. The coastal region having generally higher hazard levels than the inland cities reflects the higher precipitation through the meteorological indices (see Fig. 3). The geological and hydrological indices highlight the susceptibility of low-lying and/or urbanised areas to flooding. Table 7 summarises the statistical results for the nine PRD cities. Jiangmen, Guangzhou, Dongguan, Huizhou and Zhongshan have over 1000 km² areas in the high flood hazard zone, representing approximately 34%, 28%, 49%, 10%, and 62% of their respective land areas. Zhuhai and Zhongshan have higher percentages of their land areas (> 70%) in the relatively high and high zones, owing to their geographical location and flat terrain. Conversely, Zhaoqing and Huizhou are generally lower in their overall flood hazard levels. This is broadly consistent with the ranking based on the number of surface water flooding incidents reported in the PRD cities between 2012 and 2014 (Huang et al., 2017), where Guangzhou, Dongguan, Shenzhen, and Zhongshan were the top four whilst Jiangmen and Zhaoqing had the lowest occurrences.

4.1.1 Validation using reported surface water flooding hotspots

We next compared the flood hazard map with publicly available information on the spatial distribution of surface water flooding hazards of the region as a validation. As the derived flood hazard map represents the long-term characteristics of the flooding likelihood in the study area, we use the reported surface water flooding hotspots as it highlights the areas that are exposed to frequent flooding from several rainfall events. Huang et al. (2017) reported locations of surface water flooding hotspots across PRD in 2014 which is replotted and overlaid on our hazard map in Fig. 7. It is evident that these reported hotspot clusters are well captured by the flood hazard map, demonstrating the adequacy of the indices and their grading standards used in deriving the map. Over 77.01% of the 348 reported hotspots fall within the relatively high and high zones of the derived flood hazard map (Table 8). The hotspots tend to cluster in city or district centres due to expected reporting bias for surface water flooding events. Given that few reports on the long-term surface water flood depths are available publicly for the region, this regional flooding hotspots comparison can be regarded as a good qualitative agreement on surface water flooding potential in the urbanised areas of the region.

Further comparisons were carried out at city-level for Shenzhen and Zhuhai, and at sub-city level for Zhongshan in Fig. 8. This is based on data from different reporting sources for 2014-2015 (listed in Fig. 8). It can be observed that surface water flooding is a widespread issue in highly urbanised Shenzhen (Fig. 8(a)) where most of the low-lying areas are prone to flooding. This is particularly evident in the northwestern and southern parts of Shenzhen, most of which were developed over 10-20 years ago. The reported incidents generally fall within the zones of higher hazard levels, with 77.23% of the 439 reported hotspots falling under the relatively high and high zones of the derived flood hazard map (Table 8). In addition, the obvious differentiation between the hazard levels in Shenzhen allows for a clear indication of the areas subjected to higher hazard levels. Table 7 suggests that Zhuhai has the highest percentage of land area in the high hazard zone in the PRD, most of which are concentrated

in the western and southwestern part—an alluvial plain near the river outlets formed primarily by silt accumulation and reclamation work (Fig. 8(b)). The terrain profiles are most prone to surface water flooding due to low capacity for infiltration and high tendency for water accumulation. While most of the reported flood hotspots fall under the relatively high and high zones of the hazard map (as shown Table 8), the similarity in the land environment for most parts of the city led to less differentiation in flood hazard characterisation, with most of the grids are clustered in the relatively high and high hazard zones. The central district of Zhongshan city is enclosed by crisscrossing river reaches as shown in Fig. 8(c). This close proximity to waterbodies makes the area generally fall in the high hazard zone. The historical flood data indicate that the hazard is quite widespread in the flat area of the central district.

The level of agreement between the developed flood hazard map and reported surface flooding events at city or sub-city level in Figs. 7 and 8 is highly encouraging, given the spatial scale of the input datasets, complexity involved in urban flooding, and the nature of the fuzzy comprehensive evaluation method. Higher spatial resolution of topographical datasets, more details on the drainage capacity at sub-city level, and refined grading standards tailoring to each individual city should enable a better depiction of the flood hazard at finer scale.

4.1.2 Validation using processed GAR15 flood hazard map

Fig. 9 presents the processed GAR15 riverine hazard map for the PRD region where the expected flood extent is highlighted in red. It can be seen that this flood extent is generally captured by the relatively high and high hazard zones in our derived flood hazard map shown in Fig. 6. This is especially evident in areas adjacent to the major river networks in Guangzhou, Zhongshan, and Jiangmen in the west, and in Huizhou and Dongguan in the east. We observe that the flood hazard near the reaches in the mountainous regions in Zhaoqing and Huizhou is not well reflected in our flood hazard map. This is due to their location in the upstream stretch of the PRD region where the riverine flooding is driven primarily by high incoming streamflow which is not included in our hazard indices used.

Table 7. Area and percentage values under different hazard levels for the nine PRD cities.

City	Area (km ²) and percentage (%) of the total area for each hazard level				
	Low	Relatively low	Moderate	Relatively high	High
Guangzhou	2677 (39.57%)	806 (11.91%)	1250 (18.47%)	126 (1.86%)	1907 (28.19%)
Shenzhen	640 (36.07%)	80 (4.51%)	128 (7.22%)	623 (35.12%)	303 (17.08%)
Zhuhai	316 (25.94%)	5 (0.41%)	37 (3.04%)	24 (1.97%)	836 (68.64%)
Foshan	1660 (46.76%)	848 (23.89%)	231 (6.50%)	172 (4.85%)	639 (18.00%)
Huizhou	5383 (49.78%)	774 (7.16%)	2412 (22.30%)	1174 (10.86%)	1071 (9.90%)
Dongguan	372 (16.12%)	297 (12.87%)	389 (16.86%)	117 (5.08%)	1132 (49.07%)
Zhongshan	267 (16.41%)	80 (4.92%)	151 (9.28%)	122 (7.50%)	1007 (61.89%)
Jiangmen	3349 (38.45%)	676 (7.76%)	1086 (12.47%)	625 (7.18%)	2974 (34.14%)
Zhaoqing	13,532 (94.04%)	136 (0.95%)	341 (2.37%)	5 (0.03%)	375 (2.61%)

Table 8. Number and percentage of the reported hotspots under different hazard levels of the derived flood hazard map as shown in Figures 7 and 8.

Region/City	Total number of reported hotspots	Number and percentage (%) of hotspots under each hazard level				
		Low	Relatively low	Moderate	Relatively high	High
PRD region (Fig. 7)	348	40 (11.49%)	16 (4.60%)	24 (6.90%)	40 (11.49%)	228 (65.52%)
Shenzhen (Fig. 8(a))	439	47 (10.70%)	31 (7.06%)	22 (5.01%)	224 (51.03%)	115 (26.20%)
Zhuhai (Fig. 8(b))	59	7 (11.86%)	0 (0.00%)	1 (1.70%)	4 (6.78%)	47 (79.66%)
Zhongshan city centre (Fig. 8(c))	36	2 (5.55%)	1 (2.78%)	1 (2.78%)	1 (2.78%)	31 (86.11%)

4.2 Assessing the socio-economic exposure at risk

A more relevant implication of the flood hazard map is an assessment of the socio-economic exposure at risk. We have used population and GDP as exposure proxies as they are the most readily available datasets reflecting exposures on society and national wealth. We next mapped them to the derived flood hazard map. The population and GDP density datasets from the Resources and Environment Science Data Center of the Chinese Academy of Sciences (<http://www.resdc.cn/>) with a grid resolution of 1 km × 1 km for year 2015 are used for the assessment.

Fig. 10(a) presents the population potentially exposed to the five levels of flood hazard at the nine PRD cities. Focusing on the relatively high and high flood levels, Guangzhou tops the list with over 8.3 million people in these zones, followed by Shenzhen (6.3 million) and Dongguan (5.1 million). Apart from Shenzhen, most of these exposed population are located in the high flood zones with 8.1 million for Guangzhou and 4.7 million for Dongguan, respectively. It is also evident that the spatial distribution of the population alters the potential for flood damage in highly urbanised cities where extensive human activities take place. We further break down the population density dataset by selecting only the grids that exceed certain threshold values (Pop_d , per km²) to focus on the highly urbanised areas and their respective flood hazard levels. Fig. 10(b) plots the distribution of the total population of the city (in %) in each flood hazard zone considering only the grids (and thus areas) that have a population density (Pop_d) ≥ 0 (i.e. all grids or areas), ≥ 1000 , ≥ 5000 and $\geq 10,000$, respectively. For Guangzhou, Shenzhen, Dongguan, and Zhongshan, the highly ($Pop_d \geq 1000$ and $Pop_d \geq 5000$) and extremely ($Pop_d \geq 10,000$) populated areas are generally exposed to relatively high and high flood hazard. Taking Guangzhou as an example, the White Paper on Water Affairs in Guangzhou (2013) (Guangzhou Water Authority, 2014) listed its main surface water flooding prone districts as Tianhe, Baiyun, Haizhu, Yuexiu, and Liwan. This coincides with the most populated districts in Guangzhou, specifically Yuexiu, Haizhu, Tianhe, and Liwan which were ranked as top four based on their reported population densities in 2015 (Guangzhou Bureau of Statistics, 2016).

The flood hazard levels for areas with a population density larger than 5000 per km² in the PRD region are shown in Fig. 11(a). It can be seen that the majority of these populous areas are located in city centres that generally corresponds to early development zones and older districts based on the regional statistical yearbooks (Guangdong Bureau of Statistics, 2018). Most of these places are also located along the major river networks as waterways were attractive locations for early human settlements in the region. Similarly, Fig. 11(b) presents the spatial distribution of flood hazard levels for areas with a GDP density larger than 10,000 RMB/km². It can be seen that the majority of the regional GDP are from the more developed cities, namely Guangzhou, Foshan, Zhongshan, Zhuhai, Dongguan, and Shenzhen, which are concentrated on floodplain near major river networks and/or coastal regions along the Pearl River estuary. Fig. 11 therefore highlights the high flood hazard potential faced by areas of high exposure of population and economic wealth in the PRD region. With the increasing urbanisation, the natural capacity for infiltration and storage that could absorb stormwater or slows the rate at which stormwater enters into drainage system greatly reduces. At the same time, ageing drainage system in these early development zones also becomes less adequate. Lastly, as most of the city centres in the PRD region are located near major river networks, their discharge into rivers primarily rely on gravity. As water levels in the river network may become elevated due to rainfall upstream, this could impede rainfall runoff being discharged into rivers which in turn may become sources of overflowing and ponding (Zhang et al. 2015).

The exposed GDP to the five flood hazard levels and their breakdown by the GDP density are shown in Fig. 12. We observe a very similar ranking of the GDP at risk to that of the population for the nine PRD cities. This is expected given the dominance of the secondary and service sectors in the regional economy. The distribution of the exposed GDP in Fig. 12(b) suggests that the economic activities in most PRD cities are potentially faced with high impact from extreme rainfall events: 20-40% on average and over 50% for flood prone cities such as Guangzhou, Zhuhai, Dongguan and Zhongshan. The only exception is Zhaoqing where the exposed GDP to high hazard level is smaller than 10%.

4.3 Limitations and improvements

In the preceding sections, it is shown that the flood hazard in the highly urbanised PRD cities is strongly correlated to human activities through modifications of the natural infiltration and conveyance of received precipitation. While the rainfall patterns remain largely stable at short time horizon, the urban landscape can undergo constant and/or rapid change owing to continuous economic development. As such, the robustness of the flood hazard evaluation for accommodating temporal and spatial variations of the localised urban landscape becomes crucial. Given the nature of fuzzy comprehensive method which relies heavily on the selected indices and their grading standards, limitations are inevitably embedded in the methodology and input data used. Firstly, our grading of indices representing the terrain profiles (elevation and terrain slope) is at city level. This assumes that the topographic lows are likely to be subjected to higher flood hazard. However, several drainage basins may exist in a city area that allow for different routings for stormwater conveyance, and only the true topographic lows in each basin will be potentially prone to high flood hazard. Thus, more detailed watershed delineation to differentiate the draining characteristics will improve the clustering of hazard levels observed in Fig. 8(b) and (c). Secondly, as the evaluation was conducted at the regional level, the resolution of some input datasets was aggregated to a coarser resolution with the grading standards applied at city/regional levels. This inherently reduces the sensitivity to meteorological, geological and hydrological characteristics at local level. While the obtained hazard map is

adequate for flood hazard mapping at the designed level, a smaller grid size to preserve the terrain profile from the input datasets would be preferred for better depiction of the local topography. Lastly, we have only considered drainage in urban areas as guided by the level of details from the data available. Other datasets can be sourced to further describe the variation in the drainage. For example, information on the design standard may be inferred from the year of urbanisation of the area, and spatial distribution of the open conveyance channels, stormwater pump stations, and storage facilities can further inform the local variations in surface water runoff movement beyond the urban areas.

5. Conclusions

This paper presents a set of indices for assessing the flood hazard of a highly urbanised area using the fuzzy comprehensive evaluation method. A total of seven indices are selected based on the rainfall-runoff process such that the meteorological (maximum 1-day precipitation and annual average number of heavy precipitation days), geological (elevation and terrain slope), and hydrological characteristics (soil type, runoff coefficient, and proximity to waterbodies) of the study area can be represented. We further modify the surface runoff coefficient of the urbanised areas derived simply from the land cover information with drainage pipeline density data to address the varying levels of drainage capacity in the area of concern.

We demonstrate the adequacy of this approach by applying the methodology on evaluating the pluvial flood hazard of the Pearl River Delta region, consisting of nine cities in Guangdong province, China. Extensive input datasets covering meteorological, topographic, hydrological, and socio-economic data have been used. We compared the developed flood hazard map (1 km spatial resolution) against the reported surface water flooding events in the literature and riverine flood hazard map of the PRD region from the 2015 Global Assessment Report. The hazard map shows similar spatial patterns to those reported for surface water flooding hotspots in urbanised areas and to the riverine flood hazard map. Further analysis of the regional socio-economic profiles suggests that most of the PRD cities are potentially faced with high impact from flood hazard, with estimates of close to 23 million people and 2.4 trillion RMB GDP exposed to high flood hazard. Mega cities, Guangzhou and Shenzhen, top the city ranking as over 20-40% of their urban settlements (area with a population density larger than 10,000 per km²) and intense economic activities (area with a GDP density over 10,000 RMB per km²) are located in the high flood hazard zone.

The flood hazard map for the PRD region highlights the potential impact of human activities on the flood hazard and flood risk owing to the concentration of population and wealth in urban cities. With the increasing numbers of open data becoming available from remote sensing and crowdsourcing, the proposed approach can be further improved and/or downscaled to higher resolutions for better evaluation of the local stormwater routing and accumulation. It can be used as a robust assessment tool for regular and adequate evaluation of present flood hazard, projection of future flood hazard from land use changes for planning purpose, and support the decision making of disaster risk management.

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Figure 1. The administrative divisions of the PRD region. The three major river networks in the PRD region, Xi Jiang (West River, in red), Bei Jiang (North River, in green) and Dong Jiang (East River, in purple) are highlighted.

Figure 2. Distribution of weather stations in the PRD region used for analysis of the maximum 1-day precipitation index (M1DP) and their corresponding record lengths (the end year of the datasets is 2011). The coverage of the gridded daily precipitation datasets used for calculating the average number of heavy rainfall days per year (AHPD) is shown at a resolution of 0.5°.

652 **Figure 3.** Spatial distributions of the meteorological index values: (a) Maximum 1-day precipitation (M1DP)
and (b) Annual average number of heavy precipitation days (AHPD).

Figure 4. Grading of the M1DP index at city level.

Figure 5. Spatial distributions of the five indices representing the geological and hydrological characteristics: (a) elevation (EL); (b) terrain slope (SL); (c) distance to main waterbody (DtW); (d) soil type (ST); and (e) runoff coefficient (RC) based on the land use map in 2015 with modified RC values for urban areas.

Figure 6. Flood hazard map developed for the PRD region.

Figure 7. Comparison of the flood hazard map with reported surface water flooding hotspots in the PRD region (excluding four northwestern counties in Zhaoqing) in 2014. The flooding hotspots were redrawn from Figure 6 of Huang et al. (2017).

Figure 8. Comparison of the flood hazard map with reported surface water flooding hotspots in (a) Shenzhen
 670 (reported in Urban Planning, Land and Resources Commission of Shenzhen Municipality, 2016); (b) Zhuhai
 (reported in Zhuhai Housing, Urban-Rural Planning and Development Bureau, 2017); and (c) central city in
 672 Zhongshan (Nie et al., 2016).

Figure 9. Processed AAFD for the PRD region from GAR15 probabilistic riverine flood hazard maps. The extent of the potential flood zone is indicated by AAFD > 0.1 m, where the band of AAFD follows the convention of the GAR15 probabilistic riverine flood hazard maps.

678 **Figure 10.** (a) Population exposed to different flood hazard levels in each PRD city and (b) the distribution
680 (%) of municipal population exposed to the five levels of flood hazard when considering city areas with varying
degrees of population density, $Pop_d \geq 0, 1000, 5000$ and $10,000$ per km^2 , respectively.

Figure 11. Flood hazard map for areas with (a) population density, Pop_d , larger than 5000 per km^2 and (b) GDP density, GDP_d , larger than 10,000 RMB per km^2 .

686 **Figure 12.** (a) GDP exposed to different flood hazard levels in each PRD city (in RMB) and (b) the distribution
688 (%) of municipal GDP exposed to the five levels of flood hazard when considering city areas with varying
degrees of GDP densities, $GDP_d \geq 0$, 1000, 10,000 and 100,000 RMB per km^2 , respectively.

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