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DOI
10.1016/j.jhydrol.2021.126393

Publication date
2021

Document Version
Final published version

Published in
Journal of Hydrology

Journal of Hydrology 599 (2021) 126393

Contents lists available at ScienceDirect

Journal of Hydrology

journal homepage: www.elsevier.com/locate/jhydrol

Research papers

Identification of sensitivity indicators of urban rainstorm flood disasters: A case study in China

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ARTICLE INFO

This manuscript was handled by J. Simunek, Editor-in-Chief, with the assistance of Jiri Simunek, Associate Editor

Keywords:
Urban flood
Urban element
Random Forest
Economic loss
Relative importance

ABSTRACT

Urban rainstorm floods have become one of the most significant natural disasters that restrict the healthy development of the economy and society. It is imperative to reduce the risk of urban rainstorm flood disasters, which is growing along with urbanization, during the process of urban planning and construction. However, because of the complexity of urban elements, it is quite difficult to identify sensitive indicators of urban rainstorm flood disasters to provide effective guidance on flood control. In this study, the composition of urban elements was systematically proposed based on Descriptive Framework for Cities and Communities, including natural, structural, and social elements, and then a specific indicator system was established. Furthermore, Random Forest Model was used to determine the relative importance of the indicators that are closely related to the direct economic loss that reflects the severity of urban rainstorm flood disasters. Considering four cities in China, Beijing, Tianjin, Chongqing, and Shanghai, with different topographical and hydrological conditions, as examples, the sensitivity indicators of urban rainstorm flood disasters were identified, and the results were verified based on the catastrophe evaluation method. The results indicate that urban rainstorm flood disasters are the most sensitive to surface water resources, and are the least sensitive to relief degree of land surface. Finally, specific measures to mitigate urban rainstorm flood disasters were proposed.

1. Introduction

Because of anthropogenic activities and climate change (Daksiya et al., 2021; Li and Sivapalan, 2020), urban rainstorm flood disasters have gradually become one of the most significant risks to human survival and social development (Aerts et al., 2014). According to the Ministry of Water Resources of the People's Republic of China, more than 100 cities in China suffered from urban floods every year from 2008 to 2018, causing direct economic losses of 374.5, 267.5, 315.6, and 364.3 billion yuan in 2010, 2012, 2013, and 2016, respectively. Therefore, urban rainstorm flood disasters have become a crucial problem that restricts the sustainable and healthy development of China's economy and society (Yin et al., 2015; Zheng et al., 2016).

Urban flood management has become a popular research topic, including drainage (Hellmers et al., 2017), rainstorm flood forecasting and early warning (Yan et al., 2018), storm water management and utilization (Schaer et al., 2018), and flood risk analysis (Mcclean et al., 2020). Andersen et al. (2013) demonstrated that topographic and anthropogenic influences exacerbate or reduce flood risks by altering the surface runoff, infiltration, storage, and precipitation development. Yu and Coulthard (2015) revealed the effects of catchment hydrological parameters on urban floods. Chang and Huang (2015) found that land use and land cover changes have contributed to an increase in urban flooding. Tian et al. (2019) derived critical thresholds beyond which urban pluvial flooding is likely to occur based on a decadal dataset of radar rainfall maps. Thanvisitthpon (2019) investigated the impact of land use transformation and anti-flood structural infrastructure on flooding in four flood-prone districts in Thailand. Anni et al. (2020) analyzed the role of stormwater infrastructure and soil infiltration in urban floods.

Furthermore, in addition to rainfall and the underlying surface, urban planning and management have a significant impact on urban flooding (Zhou et al., 2019). Löwe et al. (2017) proved that urban planning policies are an efficient means for urban flood reduction. Rezende et al. (2019) used socio-economic indices to analyze urban flood resilience. Li and Sivapalan (2020) analyzed the substantial role of human actions in urban floods and urban water systems. These studies revealed the impacts of some factors on urban floods to a certain extent

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https://doi.org/10.1016/j.jhydrol.2021.126393
Received 19 February 2021; Received in revised form 14 April 2021; Accepted 26 April 2021
Available online 29 April 2021

through the analysis of the physical mechanism of urban flooding. However, these studies are inadequate for complex urban systems because of their overreliance on simplistic methods at large scales (Saksena et al., 2020). With the characteristics of a highly concentrated population and facilities, complex spatial structure, high-speed dynamic operations, and evolution, urban areas are complex and vast systems coupled with nature and humanity, which is distinct from any other natural system (Li and Willems, 2020). This system consists of mutual relationships and interactions among various elements, including not only natural elements and structural elements, such as topography and underlying surface, but also social elements, such as government intervention and economic effects. Urban flood response has striking spatial heterogeneities in peak flood magnitudes, response times, and runoff ratios, which are primarily linked to the watershed scale, distribution of impervious cover, and storm water management (Zhou et al., 2019). Therefore, to identify the sensitivity indicators of urban rainstorm flood disasters, it is necessary to comprehensively analyze the related urban elements.

Urban elements cause urban flooding and economic losses when combined with rainstorms, attracting the attention of society (Ge et al., 2020). Bermúdez and Zischg (2019) explored the sensitivity of flood loss estimates to the spatial representation of buildings and hazard attribution methods. Grantham et al. (2019) described a set of climate-informed ecological resilience principles and the associated indicators to guide climate-adaptive water resource management. Lee and Brody (2019) verified that a high-density development of compact designs decreases flood loss, even though urban built-up land with higher impervious surfaces may cause more flood damage. Waghwala and Agnihotri (2019) stressed that the lack of flood management in urban areas led to increasing flood losses in urban sprawl. Pinos et al. (2020) estimated the direct damage caused by urban floods with different return periods based on a univariable deterministic flood loss model. Mei et al. (2020) found that both rainfall intensity and rainfall patterns are the determining factors of urban flooding. Despite the increase in flood hazards and exposure information accuracy, the estimation of losses is a poorly understood component of pluvial flood risk quantification (Rözer et al., 2019). However, with the increase in flood loss data and the rapid development of big data technology that explores information quickly and easily (Ge et al., 2021), the identification of sensitivity indicators of urban rainstorm flood disasters can be realized based on the actual loss, providing new ideas for urban flood disaster management.

Machine learning algorithms are increasingly being used in natural disaster risk assessments. Li et al. (2019) used four machine learning algorithms to identify flood sensitivity indicators and assessed the risk in river basins involving thirteen indicators. The results indicated that random forest (RF) performed the best in the test and could be used as an effective and reliable tool in flood sensitivity assessments.

Hence, this study established an indicator system for urban rainstorm flooding based on an urban element analysis and determined the relative importance of the indicators based on the RF algorithm to identify the urban rainstorm flood disaster-sensitive indicators, providing a reference for urban construction planning and disaster control.

2. Materials and methods

2.1. Study areas

The study focuses on four municipalities that are directly under the central government of China, that is, Beijing, Tianjin, Chongqing, and Shanghai, which play vital roles in the politics, economy, culture, tourism, and other aspects of the country. The four cities have varying topographical and hydrological conditions. The capital city, Beijing, is located in northern China. Tianjin, close to Beijing, is the largest port city in northern China. Chongqing is the largest industrial and commercial city in southwest China. Shanghai is the economic, financial, and cultural center, and located in East China. The geographical conditions of the four cities are shown in Fig. 1.

By the end of 2017, the urbanization rates of Beijing, Tianjin, and Shanghai exceeded 80%, and the urbanization rate of Chongqing increased from 48.10% to 64.08% from 2006 to 2017. In this study, data regarding the urban elements and the direct economic losses due to flooding for Beijing, Tianjin, and Chongqing from 2006 to 2017 were used as the sample data, while those for Shanghai (2012–2017) were used as the validation data. From 2006 to 2017, the proportions of the years that Beijing, Tianjin, Chongqing, and Shanghai experienced direct losses due to urban flood were 75%, 58%, 83%, and 75%, respectively, as shown in Fig. 2.

2.2. Urban rainstorm flood disaster system analysis

Urban rainstorm flood disasters are typical natural disasters that are affected by traditional hydrological factors and anthropogenic factors, such as land use, population, and wealth accumulation, resulting from urbanization.

The process of urban rainstorm flood disasters follows the chain development of natural disaster systems (Wu et al., 2020b). The rain falls into the urban system and continuously produces surface confluence from the interaction between the topography and the underlying surface. When the surface confluence exceeds the urban drainage capacity, urban flooding occurs and may cause an economic loss. The formation process of the disaster chain system divides the variables into input variables, state variables, and output variables.

As a disaster-causing factor, rainfall is an input variable. A state variable is the state of the participating factors that form the urban flood disaster, that is, the state of the urban flood and the related urban elements. Intuitively, the output variable is the disaster loss. The mode of the urban rainstorm flood disaster chain is shown in Fig. 3.

According to Fig. 3, the state of urban flooding is formed by the interaction between the rainfall and urban elements related to urban flooding, as shown in Eq. (1).

$$F = \{R, U\} \tag{1}$$

where F is the urban flood state, and R and U are the states of the rainfall and urban elements related to urban flooding, respectively.

The loss due to urban rainstorm flood disasters is caused by urban flooding and urban elements, as shown in Eq. (2).

$$L = \{F, U\} \tag{2}$$

where L is the urban flood disaster loss.

Hence, the loss due to urban rainstorm flood disasters is directly determined by the rainfall and the states of the urban elements, as shown in Eq. (3).

$$L = \{R, U\} \tag{3}$$

2.3. Urban elements analysis

In response to the needs of the United Nations (UN), World Bank, Organization for Economic Co-operation and Development (OECD), and other international organizations and countries for urban sustainable development standards, the Sustainable Cities and Communities of the International Organization for Standardization (2019) established the standard of the 'Descriptive Framework for Cities and Communities (ISO/DIS 317105)', which uses the analogy between the human anatomy and dynamic physiology to describe cities, also known as the urban anatomy. This standard outlines that the city can be understood as an ecosystem, which can be divided into three parts: the living entity in the ecosystem, the physical structure, and the interaction between the two (Lin and Xia, 2013). The living entity refers to human beings, and the physical structure refers to the composition of physical factors that ensure all the human activities in the city, which is manifested as the physical structure of the city. The interaction between them is

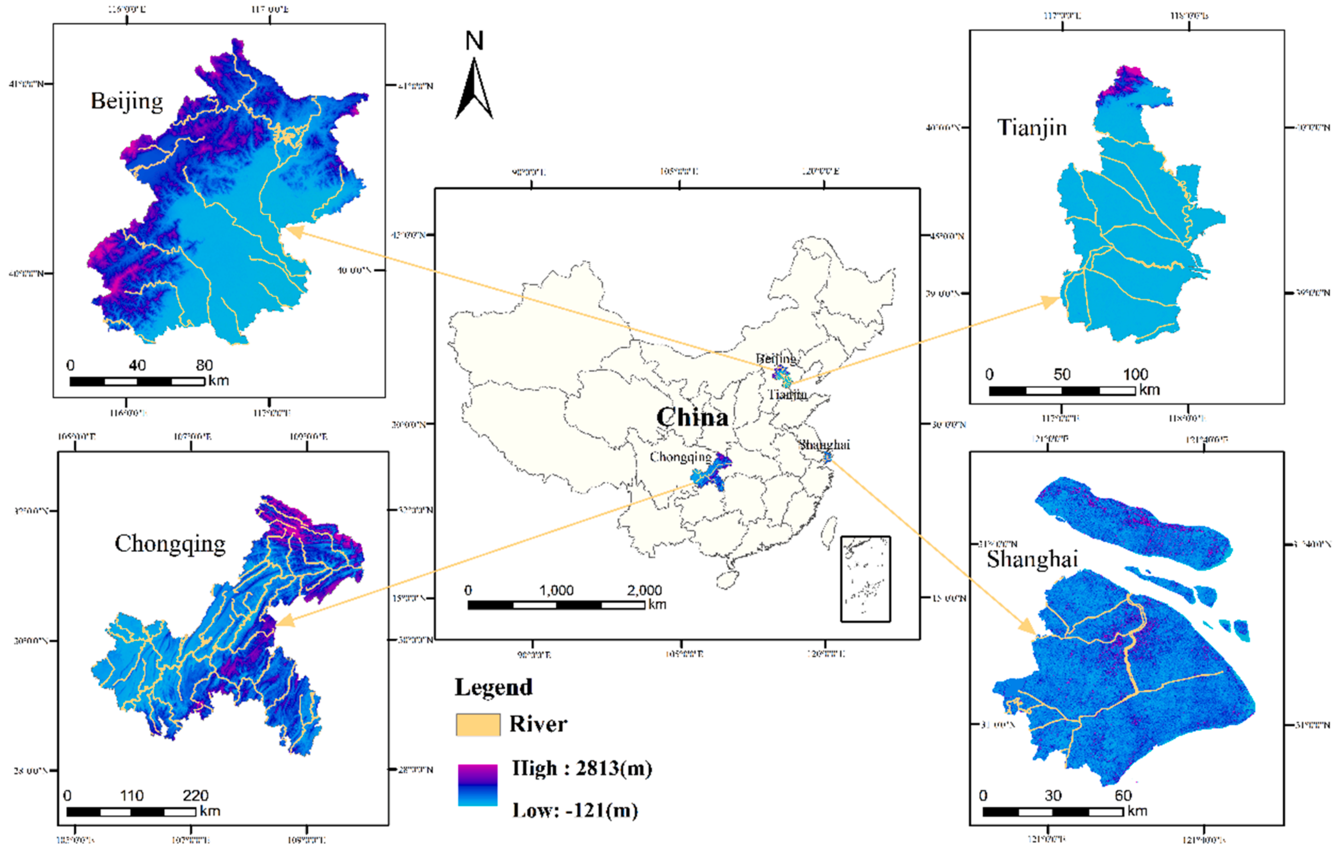

Fig. 1. The four study areas in China.

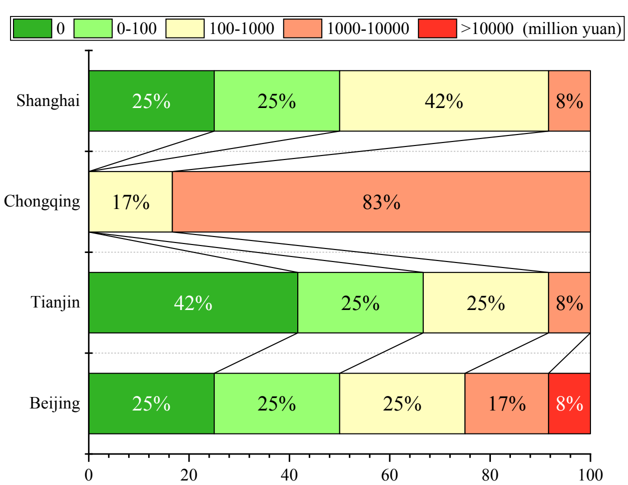

Fig. 2. The distribution of direct economic loss caused by flood in four cities from 2006 to 2017.

manifested mainly as social elements, including life, work, education, economy, culture, and information. Hence, the urban system structure can be determined, as shown in Fig. 4.

Urban rainstorm flood disasters result from the interaction between rainfall and the elements of the urban system structure. Rainfall is also a natural factor that can be attributed to the natural elements of urban floods. Hence, the types of urban elements associated with urban rainstorm flood disasters can be determined, which are divided into natural elements, structural elements, and social elements, as shown in Fig. 5.

According to Fig. 5, the indicators used to characterize the urban system elements related to urban rainstorm disasters can be determined.

2.3.1. Natural elements

According to the urban system structure, natural elements are the constituent elements of the natural environment. Urban anatomy defines the natural environment as a natural system composed of water, earth, and air, which supports the formation and development of cities (International Organization for Standardization, 2019). Therefore, natural elements include rainfall, surface water resources, and topography. Because floods occur more frequently during the warm seasons (Amann et al., 2015), for example, from June to September in China, the accumulated rainfall during the flood season (ARFS) was adopted to indicate the urban rainfall conditions. Surface water resources (SWRs) are the urban surface water resources. The relief degree of the land surface (RDLS) is a macroscopic index used to describe the terrain characteristics of a region and is used to express the difference between the altitudes of the highest point and the lowest point in a specific region. According to the definition of the RDLS, an altitude of 500 m was regarded as the height of China's benchmark mountain (Feng et al., 2008). The RDLS could then be calculated, as shown in Eq. (4).

$$RDLS = [Max(H) - Min(H)] \times [1 - \frac{P(A)}{A}]/500 \quad (4)$$

where $Max(H)$ and $Min(H)$ are the highest and lowest elevations (m) in the region, respectively, $P(A)$ is the flat area (km^2) in the region, and A is the total area of the region.

2.3.2. Structural elements

According to the urban system structure, structural elements are components of the construction environment. Urban anatomy defines the construction environment as a physical facility environment established based on the natural environment to meet the needs of human survival and sustainable development, which maintains the rapid and stable operation of urban areas (International Organization for Standardization, 2019). Therefore, structural elements are divided into four

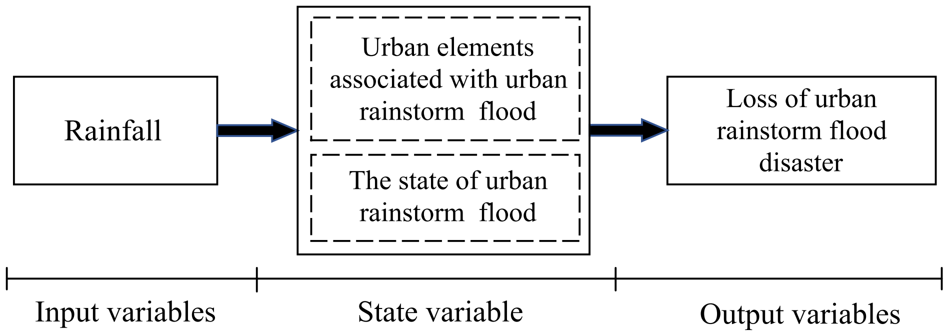

Fig. 3. The mode of urban rainstorm flood disaster chain.

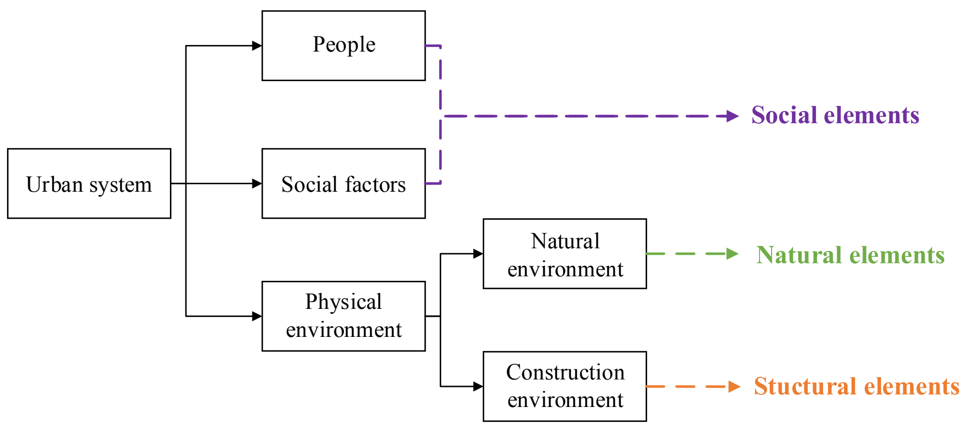

Fig. 4. Urban system structure.

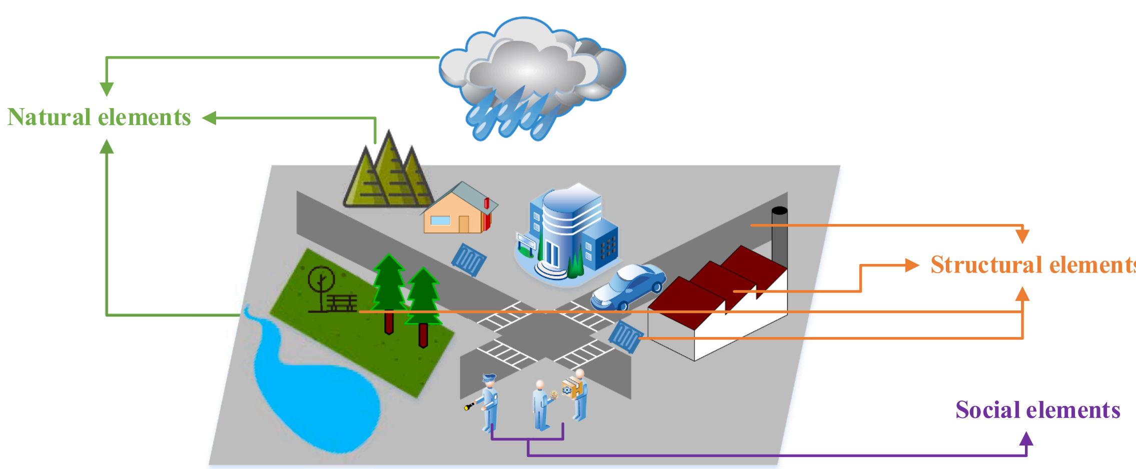

Fig. 5. Urban system elements related to flood disaster.

categories: construction area, green facilities, transport facilities, and water circulation facilities (Xiang, 2014). The construction area was represented by the proportion of the built-up area (PBA) and construction land. According to the 'China Construction Statistical Yearbook', the proportion of construction land includes the proportions of residential land (PRL), public management and service land (PPMSL), industrial land (PIL), logistics, and storage land (PLSL), which are equal to the proportion of the area of the corresponding land type to the total urban area (Wu et al., 2020b). Green facilities are represented by the green coverage rate (GCR). Urban transport facilities primarily include roads, railways, and intersections (Chen et al., 2020). Therefore, the road area rate (RAR), density of the road network (DRN), urban rail transit system (completed) (URTS(C)), urban rail transit system (under construction) (URTS(U)), and number of intersections (NI) were adopted (Wu et al., 2019). The water circulation facilities related to urban rainstorm floods are predominantly urban drainage pipe networks, which are represented by the density of sewers (DS).

2.3.3. Social elements

Urban anatomy defines social elements as interaction products between people and the construction environment (International Organization for Standardization, 2019). Therefore, social elements are primarily composed of people, the government, and their derivatives. People can be divided into the managers (i.e., government) and managed (i.e., residents) and were represented by the population density (PD). The government refers to the body of state's rule and social management, and their effective prevention and emergency management play positive roles in urban rainstorm floods and the number of government employees (NGE) in water conservancy and municipal industries. Urban gross domestic product (GDP) was selected because economic loss was considered as an indicator of flood loss in this study.

Hence, an indicator system for urban elements that are closely related to urban flooding was established, as shown in Fig. 6. All the indicator data were extracted from the 'China Urban Construction Statistical Yearbook', 'Urban Water Resources Bulletin', and 'China Flood and Drought Disaster Bulletin' (Wu et al., 2020b).

2.4. Random Forest model

RF is a machine learning algorithm proposed by Leo Breiman (2001), which combines the bagging ensemble learning theory with the stochastic subspace method. Currently, the algorithm has been widely used because of its good performance, such as the identification of the association of gene sequences in the field of biological information (Boulesteix et al., 2012), the recognition of the most important environmental variables in the ecological distribution of species and populations (Ellis et al., 2012), and the analysis of the impact characteristics of global change (Yu et al., 2019). Numerous theories and examples have demonstrated that RFs have strong data mining ability and high prediction accuracy, with a good tolerance for outliers and noise. It has good scalability and parallelism for high-dimensional data classification problems without being prone to overfitting and is known as one of the best algorithms at present (Iverson et al., 2008).

2.4.1. Model building process

RF is an ensemble learning model based on a decision tree. It contains multiple decision trees trained using bagging ensemble learning technology. When the samples to be classified are input, the final classification result is determined by voting on the output of a single decision tree. In addition, RF is a data-driven nonparametric classification method, which only needs to train the classification rules by learning the given samples without prior knowledge.

RF is a classifier composed of a series of tree classifiers. The generating steps are shown in Fig. 7. (1) Select k sub-training sample sets with bootstrap sampling from the input urban rainstorm flood loss and urban factors sample sets, and pre-build K classification trees; (2) select the optimal segmentation indicator on each node of the classification tree for segmentation; (3) repeat step (2) until the pre-built K taxonomic trees are traversed; (4) RF is formed by K taxonomic trees. The input training sets were obtained by bootstrap random sampling, and the indicators of the classification tree nodes were segmented randomly, ensuring that the correlation between the classification trees was reduced. A single tree without pruning can obtain a low-deviation classification tree, ensuring the accuracy of the results.

2.4.2. Analysis of the relative importance of urban element indicators

The program recursion method is typically adopted to generate the decision trees. The root node splits and generates two subtrees, that is, the left and right subtrees. Then, the subtrees will not stop generating new nodes and subtrees until the leaf nodes are generated. To choose the best split mode, the split results should be compared when the subtrees are generated because different split modes cause distinct results. Hence, the selection of the decision tree generation algorithms that correspond

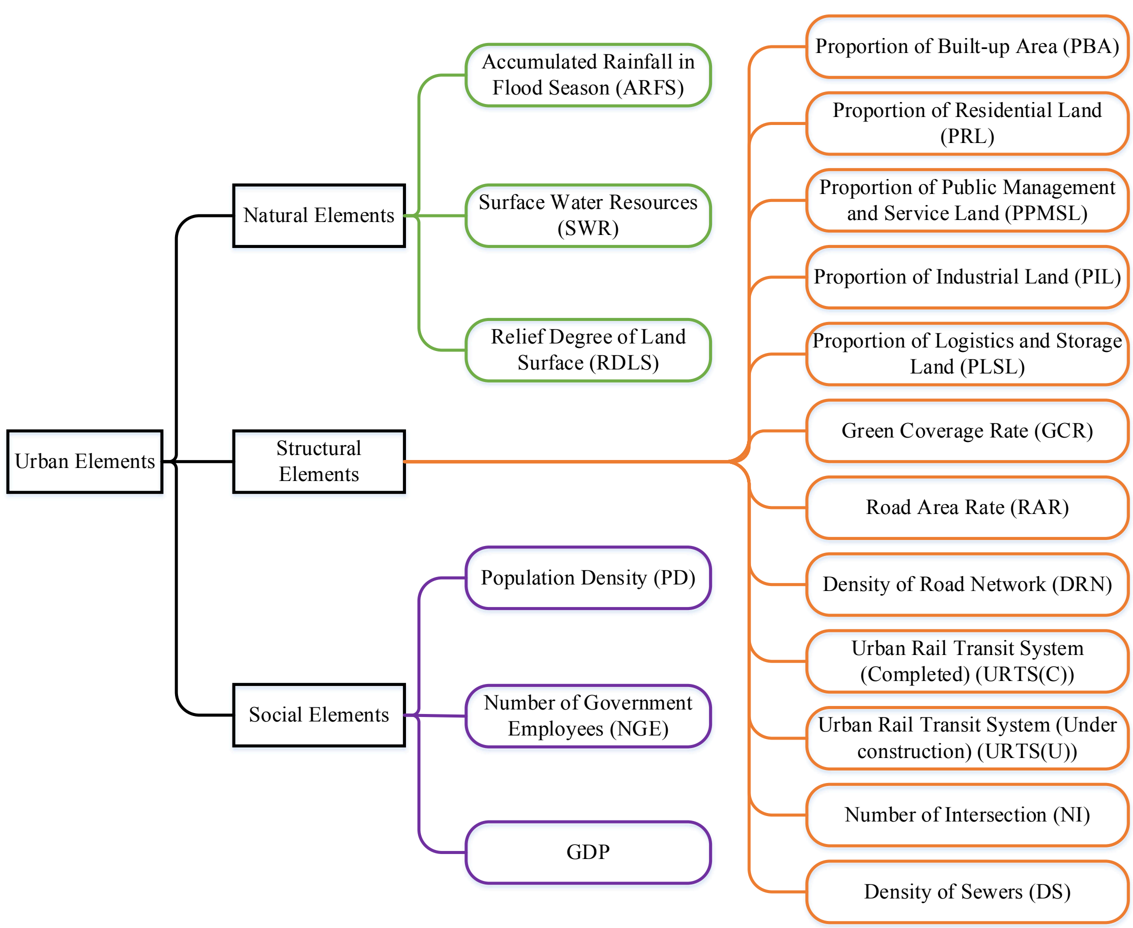

Fig. 6. Indicator system of urban elements.

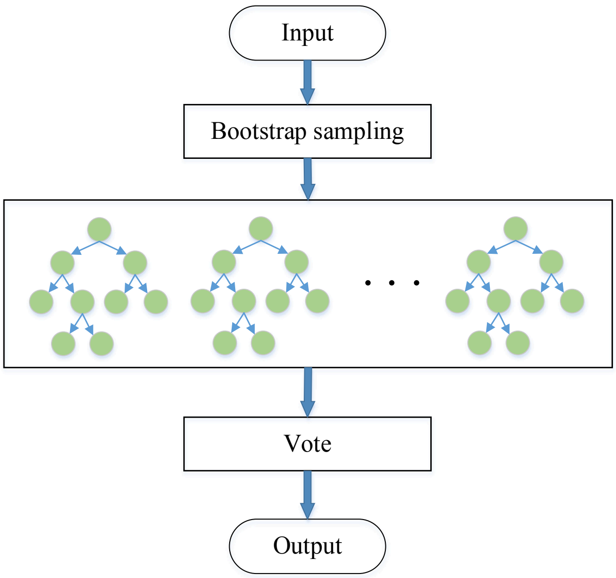

Fig. 7. The process of Random Forest.

to the comparison rules is critical in this process. The CART algorithm, which has been further optimized to solve classification and regression problems based on other algorithms, deals with discrete attribute variables efficiently and reasonably (Yu et al., 2019). Therefore, the CART algorithm was adopted to determine the split mode.

In the analysis of the relative importance of the urban element indicators associated with urban rainstorm flood disasters, the node Gini coefficient represents the impurity, as shown in Eq. (5).

$$Gini(f) = \sum_{d=1}^{k} p_d(1-p_d) = 1 - \sum_{d=1}^{k} [p(d/f)]^2 \tag{5}$$

where $Gini(f)$ is the Gini coefficient of node f, and the smaller $Gini(f)$, the lower the impurity, meaning that the sample data at node f tend toward the same disaster level; the larger $Gini(f)$, the higher the impurity, meaning that the sample data at node f tend to be evenly distributed, and less useful information is obtained; $p(d/f)$ is the probability of a disaster grade d at node f.

The importance of the urban element indicator U_j on node f is the change in the Gini index when f splits, as shown in Eq. (6).

$$VIM_{jf}^{(Gini)} = Gini(f) - Gini(l) - Gini(r) \tag{6}$$

where $VIM_{jf}^{(Gini)}$ is the importance of the urban element indicator U_j on node f, and $Gini(l)$ and $Gini(r)$ are the Gini indices of the two new nodes generated by node f splitting, respectively.

If the nodes in decision tree i composed of urban element indicator U_j belong to set M, the importance of U_j in decision tree i can be calculated according to Eq. (7).

$$VIM_{ij}^{(Gini)} = \sum_{f \in M} VIM_{jf}^{(Gini)} \tag{7}$$

where $VIM_{ij}^{(Gini)}$ is the importance of U_j in the decision tree i.

If there are n trees in RF, then:

$$VIM_{j}^{(Gini)} = \sum_{i=1}^{n} VIM_{ij}^{(Gini)} \tag{8}$$

where $VIM_{j}^{(Gini)}$ is the importance of U_j in all the decision trees.

Finally, the relative importance of the urban element indicator U_j in urban rainstorm flood disasters can be obtained by normalization, as shown in Eq. (9).

$$VIM_j = \frac{VIM_j^{(Gini)}}{\sum_{j=1}^{J} VIM_j^{(Gini)}} \tag{9}$$

Where VIM_j is the relative importance of U_j in an urban rainstorm flood disaster

and the sum $VIM_j$of all indicators is 1.

3. Results and discussion

3.1. Results and verification

Taking the flood losses of Beijing, Tianjin, and Chongqing from 2006 to 2017 as examples, the RF model was used to analyze the relative importance of the specific indicators of natural elements, structural elements, and social elements. The results are provided in Fig. 8.

To verify the accuracy of the results, the catastrophe evaluation method was used to evaluate the risk of urban rainstorm floods in Shanghai from 2012 to 2017. The catastrophe evaluation method was systematically expounded by French mathematician Rene Thom (1977) and has been widely used in the quantitative analysis of non-equilibrium phase transition processes (Chen et al., 2016) and serves water resource assessments well (Wu et al., 2020a). The catastrophe evaluation method adopts a recursive calculation to determine the value of the upper index according to the basic index values. When there is no obvious connection among the basic indicators, the upper index value is equal to the minimum value of the standardized basic index values; when there is an obvious connection between the basic indicators, the upper index value is equal to the average value of the standardized basic index values. Based on the relative importance of the indicators in Fig. 8, a systematic risk assessment was conducted. A comparison between the risk assessment results and actual losses is shown in Table 1.

According to Table 1, the rank of the catastrophe evaluation results is highly consistent with the actual direct economic losses, except for 2015. Owing to the characteristics of the catastrophe evaluation method, the risk assessment results will have a large deviation when the indicator score is the maximum or the minimum, that is, 1 or 0 (Ge et al., 2019). The score of the natural element in 2015 was 1, causing it to be ranked first in the catastrophe evaluation results. When this singularity is eliminated, the rank of the evaluation results is completely consistent with the actual losses, which shows that the relative importance of urban element indicators analyzed based on the RF model is reasonable.

3.2. Discussion

According to Fig. 8, the SWR is the most significant indicator of the natural elements that cause urban rainstorm flood disasters. Because the flood storage capacity of an urban area will not change significantly in the short term, the more SWR of the urban area, the less spare flood storage capacity, and the higher the flood disaster risk. Furthermore, ARFS also plays a critical role in urban rainstorm flood disasters, which is consistent with the results of Ji et al. (2013). However, the RDLS is much less important than the SWR and ARFS, even though a higher RDLS results in a higher flood risk (Ji et al., 2013). As a long-term stable natural condition, the RDLS of an urban area cannot change greatly over decades, leading to little effect on the urban rainstorm flood losses. Combined with the relative importance of the three indicators and whether they are easy to control, the most effective urban flood disaster risk management measure is improving the accuracy of rainfall forecasting and the early warning ability of urban rainstorm flood risk.

The PBA has the highest relative importance among the structural elements, indicating that the higher the degree and concentration of urban development and construction, the higher the flood disaster risk. Except for the PBA, the PRL is much more significant than other indicators, because transportation, personnel, and economy gather around residential land in China, increasing the difficulty in disaster relief and

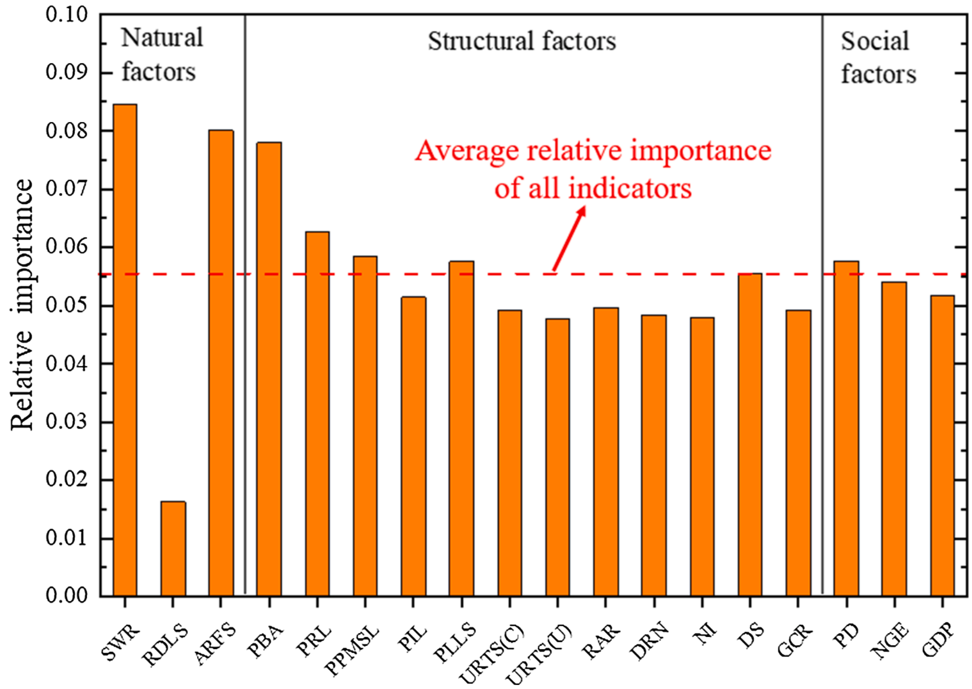

Fig. 8. The relative importance of urban element indicators.

Table 1
The comparison between the risk assessment results and the actual losses.

Year	Structural elements	Social elements	Natural elements	Catastrophe evaluation results		Direct economic losses(million yuan)	
				Value	Rank	Value	Rank
2012	0.9318	0.5774	0.8001	0.9146	3	664.00	2
2013	0.9254	0.6201	0.8088	0.9210	2	1003.00	1
2014	0.7215	0.6771	0.3435	0.8310	6	0.00	6
2015	0.9691	0.6790	1.0000	0.9544	1	285.00	3
2016	0.8239	0.7460	0.4800	0.8823	4	28.00	4
2017	0.5183	0.7817	0.6514	0.8465	5	12.00	5

the intensity of disaster losses. Furthermore, both the proportions of public management and service land (PPMSL) and logistics and storage land (PLSL) are highly important. However, because industrial land is mostly located at the edge of the city and the density of the surrounding population is small, the proportion of industrial land (PIL) has the least relative importance on flood disaster risk. Hence, the proportion of construction land composed of residential land public management and service land, logistics and storage land, and industrial land, has a significant effect on urban flood disaster risk, and should be planned more reasonably, for example, dispersing the population gathering areas and reducing the local PD. As the key process for a city to digest rainwater, the drainage pipeline is directly related to the formation process of urban rainstorm floods. However, according to Fig. 8, the relative importance of the DS only reaches the average level of all the indicators and is lower than expected. This can be attributed to the rapid development of China, due to which the construction of urban drainage networks cannot keep up with the development needs in many cities, limiting their role in the relief of urban rainstorm flood disasters. Therefore, the DS in China should be effectively improved to drain urban floods over time to reduce potential losses.

The PD has a higher correlation with the flood loss compared with other indicators among the social elements, which indicates that the places with high population density may have a high risk of flood losses, which is consistent with the high importance of the PBA. In addition, the NGE has an effect on the magnitude of flood losses. The greater the investment in human resources in related industries, the higher the management and construction of related work in the region, which has a positive effect on the reduction of flood losses. Therefore, increasing the input of staff in water conservancy and municipal management is necessary, especially in low-lying and residential areas.

4. Conclusions

Based on the formation of urban flood losses, the urban elements related to urban rainstorm flood disasters were proposed, that is, natural elements, structural elements, and social elements, and the specific indicators were analyzed. Taking four representative cities as examples, the sensitivity indicators were identified according to the relative importance analysis based on the RF model, and the results were verified by the catastrophe evaluation method.

Urban rainstorm flood disasters are much more sensitive to SWR, ARFS, PBA, PRL, PPMSL, PLSL, DS, and PD than to other indicators, and has the least sensitivity to the RDLS. In order to mitigate urban rainstorm flood disasters, considering whether the indicators are easy to control, (a) the accuracy of rainfall forecasting and early warning ability of urban rainstorm flood risks should be improved; (b) combined with the weather forecast, water in the city can be discharged in advance to reduce the SWR and create more capacity to accommodate the potential flood; (c) residential land can be scattered to reduce the PD; and (d) the DS and the input of staff in water conservancy and municipal management should be increased. However, with an increase in sample size, the accuracy of the research results will be higher. Hence, the model performance should be further tested with other urban rainstorm flood disaster data when they are available.

CRediT authorship contribution statement

Meimei Wu: Methodology, Formal analysis, Writing - original draft, Writing - review & editing. **Zening Wu:** Validation, Writing - review & editing, Supervision, Funding acquisition. **Wei Ge:** Conceptualization, Formal analysis, Funding acquisition. **Huiliang Wang:** Methodology, Investigation. **Yanxia Shen:** Conceptualization, Investigation. **Mengmeng Jiang:** Validation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This research was funded by the National Natural Science Foundation of China (Grant No. 51739009, 52079127, 51709239), and the Fund of National Dam Safety Research Center (Grant No. CX2021B01).

References

Aerts, J.C.J.H., Botzen, W.J.W., Emanuel, K., Lin, N., Moel, H.D., Michel-Kerjan, E.O., 2014. Evaluating flood resilience strategies for coastal megacities. Science 344, 473–475. https://doi.org/10.1126/science.1248222.

Amann, B., Szidat, S., Grosjean, M., 2015. A millennial-long record of warm season precipitation and flood frequency for the North-western Alps inferred from varved lake sediments: implications for the future. Quaternary Sci. Rev. 115, 89–100. https://doi.org/10.1016/j.quascirev.2015.03.002.

Andersen, T.K., Shepherd, J.M., 2013. Floods in a changing climate. Geogr. Compass 7, 95–115. https://doi.org/10.1111/gec3.12025.

Anni, A.H., Cohen, S., Praskievicz, S., 2020. Sensitivity of urban flood simulations to stormwater infrastructure and soil infiltration. J. Hydro. 588, 125028 https://doi.org/10.1016/j.jhydrol.2020.125028.

Bermúdez, M., Zischg, A.P., 2019. Sensitivity of flood loss estimates to building representation and flow depth attribution methods in micro-scale flood modelling. Nat. Hazards 92, 1633–1648. https://doi.org/10.1007/s11069-018-3270-7.

Boulesteix, A.L., Bender, A., Justo, L.B., Carolin, S., 2012. Random Forest Gini importance favours SNPs with large minor allele frequency: impact, sources and recommendations. Brief. Bioinform. 13, 292–304. https://doi.org/10.1093/bib/bbr053.

Breiman, L., 2001. Random Forests. Mach. Learn. 45, 5–32. https://doi.org/10.1023/A:1010933404324.

Chang, L.F., Huang, S.L., 2015. Assessing urban flooding vulnerability with an emergy approach. Landscape Urban Plan. 143, 11–24. https://doi.org/10.1016/j.landurbplan.2015.06.004.

Chen, C., Reniers, G., Khakzad, N., 2020. A thorough classification and discussion of approaches for modeling and managing domino effects in the process industries. Safety Sci. 125, 104618 https://doi.org/10.1016/j.ssci.2020.104618.

Chen, Y., Zhang, S., Zhang, Y., Xu, L., Qu, Z., Song, G., Zhang, J., 2016. Comprehensive assessment and hierarchical management of the sustainable utilization of urban water resources based on catastrophe theory. J. Taiwan Inst. Chem. E. 60, 430–437. https://doi.org/10.1016/j.jtice.2015.10.048.

Daksiya, V., Mandapaka, P.V., Lo, E.Y.M., 2021. Effect of climate change and urbanization on flood protection decision making. J. Flood Risk Manag. 14, e12681 https://doi.org/10.1111/jfr3.12681.

Ellis, N., Smith, S.J., Pitcher, C.R., 2012. Gradient forests: calculating importance gradients on physical predictors. Ecology 93, 156–168. https://doi.org/10.1890/11-0252.1.

Feng, Z., Tang, Y., Yang, Y., Zhang, D., 2008. Relief degree of land surface and its influence on population distribution in China. J. Geogr. Sci. 18, 237–246. https://doi.org/10.1007/s11442-008-0237-8.

Ge, W., Jiao, Y., Sun, H., Li, Z., Zhang, H., Zheng, Y., Guo, X., Zhang, Z., van Gelder, P.H.A.J.M., 2019. A method for fast evaluation of potential consequences of dam breach. Water 11, 2224. https://doi.org/10.3390/w11112224.

Ge, W., Sun, H., Zhang, H., Li, Z., Guo, X., Wang, X., Qin, Y., Gao, W., van Gelder, P., 2020. Economic risk criteria for dams considering the relative level of economy and industrial economic contribution. Sci. Total Environ. 725, 138139 https://doi.org/10.1016/j.scitotenv.2020.138139.

Ge, W., Wang, X., Li, Z., Zhang, H., Guo, X., Wang, T., Gao, W., Lin, C., van Gelder, P., 2021. Interval analysis of loss of life caused by dam failure. J. Water Res. Plan. Man. 147, 04020098. https://doi.org/10.1061/(ASCE)WR.1943-5452.0001311.

Grantham, T.E., Matthews, J.H., Bledsoe, B.P., 2019. Shifting currents: Managing freshwater systems for ecological resilience in a changing climate. Water Security 8, 100049. https://doi.org/10.1016/j.wasec.2019.100049.

Hellmers, S., Manojlovic, N., Palmaricciotti, G., Fröhle, P., 2017. Modelling decentralised systems for urban drainage and flood mitigation. J. Appl. Water Eng. Res. 5, 61–69. https://doi.org/10.1080/23249676.2015.1128368.

International Organization for Standardization. 2019. ISO/DIS 317105, Sustainable cities and communities- Descriptive framework for cities and communities.

Iverson, L.R., Prasad, A.M., Matthews, S.N., Peters, M., 2008. Estimating potential habitat for 134 eastern US tree species under six climate scenarios. Forest Ecol. Manag. 254, 390–406. https://doi.org/10.1016/j.foreco.2007.07.023.

Ji, Z., Li, N., Xie, W., Wu, Z., Yang, Z., 2013. Comprehensive assessment of flood risk using the classification and regression tree method. Stoch. Env. Res. Risk A. 27, 1815–1828. https://doi.org/10.1007/s00477-013-0716-z.

Lee, Y., Brody, S.D., 2019. Examining the impact of land use on flood losses in Seoul, Korea. Land Use Policy 70, 500–509. https://doi.org/10.1016/j.landusepol.2017.11.019.

Li, B., Sivapalan, M., 2020. Long-Term Coevolution of an urban human-water system under climate change: critical role of human adaptive actions. Water Resour. Res. 56, e2020WR027931. https://doi.org/10.1029/2020WR027931.

Li, X., Willems, P., 2020. A Hybrid model for fast and probabilistic urban pluvial flood prediction. Water Resour. Res. 56, e2019WR025128. https://doi.org/10.1029/2019WR025128.

Li, X., Yan, D., Wang, K., Wang, B., Liu, S., 2019. Flood risk assessment of global watersheds based on Multiple Machine Learning Models. Water 11, 1654. https://doi.org/10.3390/w11081654.

Lin, Z., Xia, B., 2013. Sustainability analysis of the urban ecosystem in Guangzhou City based on information entropy between 2004 and 2010. J. Geogr. Sci. 23, 417–435. https://doi.org/10.1007/s11442-013-1019-5.

Löwe, R., Urich, C., Domingo, N.S., Mark, O., Deletic, A., Arnbjerg-Nielsen, K., 2017. Assessment of urban pluvial flood risk and efficiency of adaptation options through simulations- A new generation of urban planning tools. J. Hydro. 550, 350–367. https://doi.org/10.1016/j.jhydrol.2017.05.009.

Mcclean, F., Dawson, R., Kilsby, C., 2020. Implications of using Global Digital Elevation Models for flood risk analysis in cities. Water Resour. Res. 56, e2020WR028241. https://doi.org/10.1029/2020WR028241.

Mei, C., Liu, J.H., Wang, H., Li, Z.J., Yang, Z.Y., Shao, W.W., Ding, X.Y., Weng, B.S., Yu, Y.D., Yan, D.Y., 2020. Urban flood inundation and damage assessment based on numerical simulations of design rainstorms with different characteristics. Sci. China Technol. Sc. 63, 2292–2304. https://doi.org/10.1007/s11431-019-1523-2.

Pinos, J., Orellana, D., Timbe, L., 2020. Assessment of microscale economic flood losses in urban and agricultural areas: case study of the Santa Bárbara River. Ecuador. Nat. Hazards 103, 2323–2337. https://doi.org/10.1007/s11069-020-04084-8.

Rezende, O.M., de Franco, B.R. da C.A., de Oliveira, A.K.B., Jacob, A.C.P., Miguez, M.G., 2019. A framework to introduce urban flood resilience into the design of flood control alternatives. J. Hydro. 576, 478-493. https://doi.org/10.1016/j.jhydrol.2019.06.063.

Rözer, V., Kreibich, H., Schröter, K., Müller, M., Sairam, N., Doss-Gollin, J., Lall, U., Merz, B., 2019. Probabilistic models significantly reduce uncertainty in Hurricane Harvey pluvial flood loss estimates. Earths Future 7, 384–394. https://doi.org/10.1029/2018EF001074.

Saksena, S., Dey, S., Merwade, V., Singhofen, P.J., 2020. A computationally efficient and physically based approach for urban flood modeling using a flexible spatiotemporal structure. Water Resour. Res. 56, e2019WR025769. https://doi.org/10.1029/2019WR025769.

Schaer, C., Thiam, M.D., Nygaard, I., 2018. Flood management in urban Senegal: an actor-oriented perspective on national and transnational adaptation interventions. Clim. Dev. 10, 243–258. https://doi.org/10.1080/17565529.2017.1291405.

Thanvisitthpon, N., 2019. Impact of land use transformation and anti-flood infrastructure on flooding in world heritage site and peri-urban area: A case study of Thailand's Ayutthaya province. J. Environ. Manage. 247, 518–524. https://doi.org/10.1016/j.jenvman.2019.06.094.

Thom, R., 1977. Structural stability, catastrophe theory, and applied mathematics. SIAM Rev. 19, 189–201.

Tian, X., Ten, Veldhuis. M.C., Schleiss, M., Bouwens, C., Nick, V.D.G., 2019. Critical rainfall thresholds for urban pluvial flooding inferred from citizen observations. Sci. Total Environ. 689, 258-268. https://doi.org/10.1016/j.scitotenv.2019.06.355.

Waghwala, R.K., Agnihotri, P.G., 2019. Flood risk assessment and resilience strategies for flood risk management: A case study of Surat City. Int. J. Disast. Risk Re. 40, 101155 https://doi.org/10.1016/j.ijdrr.2019.101155.

Wu, M., Ge, W., Wu, Z., Guo, X., Di, D., Huang, S., 2020a. Evaluation of the benefits of urban water resource utilization based on the Catastrophe and Emergy methods. Water Resour. Manag. 34, 1843–1853. https://doi.org/10.1007/s11269-020-02530-7.

Wu, Z., Shen, Y., Wang, H., Wu, M., 2019. Assessing urban flood disaster risk using Bayesian network model and GIS applications. Geomat. Nat. Haz. Risk. 10, 2163–2184. https://doi.org/10.1080/19475705.2019.1685010.

Wu, Z., Shen, Y., Wang, H., Wu, M., 2020b. Urban flood disaster risk evaluation based on ontology and Bayesian network. J. Hydro. 583, 124596 https://doi.org/10.1016/j.jhydrol.2020.124596.

Xiang, W., 2014. Doing real and permanent good in landscape and urban planning: Ecological wisdom for urban sustainability. Landscape Urban Plan. 121, 65–69. https://doi.org/10.1016/j.landurbplan.2013.09.008.

Yan, J., Jin, J., Chen, F., Yu, G., Yin, H., 2018. Urban flash flood forecast using support vector machine and numerical simulation. J. Hydroinform. 20, 221–231. https://doi.org/10.2166/hydro.2017.175.

Yin, J., Ye, M.W., Yin, Z., Xu, S.Y., 2015. A review of advances in urban flood risk analysis over China. Stoch. Env. Res. Risk A. 29, 1063–1070. https://doi.org/10.1007/s00477-014-0939-7.

Yu, B., Chen, F., Chen, H., 2019. NPP estimation using Random Forest and impact feature variable importance analysis. J. Spat. Sci. 64, 173–192. https://doi.org/10.1080/14498596.2017.1367331.

Yu, D., Coulthard, T.J., 2015. Evaluating the importance of catchment hydrological parameters for urban surface water flood modelling using a simple hydro-inundation model. J. Hydro. 524, 385–400. https://doi.org/10.1016/j.jhydrol.2015.02.040.

Zheng, Z., Gao, J.Q., Zhen, M., Wang, Z.F., Yang, X.Y., Luo, X.Z., Jacquet, T., Fu, G.T., 2016. Urban flooding in China: main causes and policy recommendations. Hydro. Process. 30, 1149–1152. https://doi.org/10.1002/hyp.10717.

Zhou, Z., Smith, J.A., Yang, L., Baeck, M.L., Chaney, M., Ten, Veldhuis, M.C., Deng, H., Liu, S, 2019. The complexities of urban flood response: Flood frequency analyses for the Charlotte metropolitan region. Water Resour. Res. 53, 7401–7425. https://doi.org/10.1002/2016wr019997.