AMSE JOURNALS-AMSE IIETA publication-2017-Series: Modelling C; Vol. 78; N°2; pp 210-224
Submitted Mar. 27, 2017; Revised May 10, 2017; Accepted Jun. 01, 2017

Urban Rainstorm Waterlogging Risk Assessment Based on Grey-AHP

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Abstract

The recent increase in rainstorm waterlogging disasters has acutely threatened the sustainable urban development. In this situation, it is particularly important to evaluation the risk of urban rainstorm waterlogging. Hence, the popular index system assessment was improved with grey-analytic hierarchy process (Grey-AHP), and then applied to assess the risk of rainstorm waterlogging. The improved index system consists of three levels: the target level, the criterion level and the index level. Moreover, the grey judgment matrix was constructed to evaluate the uncertain indices. Based on the Grey-AHP model, the evaluated index values fall in a relatively limited scope. The effect of the model was verified in a case study on Huangxiao River, central China's Hubei Province, with such impact factors as receiving waters, river storage capacity and runoff coefficient. The results prove the effectiveness of the proposed model, which offers a feasible method and lays the theoretical basis for urban rainstorm waterlogging risk assessment.

Key words

Rainstorm waterlogging, Risk assessment, Analytic Hierarchy Process (AHP), Grey theory.

1. Introduction

Recent years has seen a growing number of rainstorms under the global climate change, which severely impedes social management, urban operation and people's lives. The negative effect is worsened by the backward drainage infrastructure and the lack of flood control and emergency measures. As an essential way to prevent and mitigate disasters and build sponge cities [1], the risk assessment of urban rainstorm waterlogging provide details on disaster risks, explains the influence of specific factors, and gives insight to improvement of urban drainage system [2].

Much research has been done on risk assessment of rainstorm and flood disasters, yielding fruitful results on urban disaster prevention and reduction. Adriana Galderisi et al. analysed a flood in Benevento [3], Italy, and designed a nature-based solution for the compact city, seeking to reduce impervious surfaces, prevent further soil sealing, and recover the fluvial ecosystem. Based on the classical assumption of time-invariant arrival times, Elena Volpi et al. developed a simple analytical framework to provide the hydrologic consequence of any spatiotemporal distribution of excess rainfall fields [4]. Diana Reckien innovatively introduced the fuzzy cognitive map to structured, semi-quantitative assessment of climate change impacts and adaptation measures [5]. Alessandro Trigila et al. combined the bivariate statistical frequency ratio method with multivariate statistical techniques like logistic regression (LR) and random forest (RF), and implemented 5 susceptibility models for rapid shallow landslides in north-eastern Sicily [6]. With the aid of a hydrodynamic model (FloodMap-HydroInundation2D), Jie Yin et al. integrated the high resolution 2D inundation modelling and flood depth-dependent measure to evaluate the potential impact and risk of pluvial flash flood on the road network in downtown Shanghai [7-8]. Golmar Golmohammadi et al. employed a modified rainfall index to assess the effect of the soil and water assessment tool (SWAT) model in predicting the temporal variation of flow sources across the watershed [9]. Based on numerical modelling, Elisabetta Napolitano et al. proposed the hydrological and stability modelling of typical ash-fall pyroclastic soil slopes in the Sarno Mountains, aiming to assess how the seasonal hydrological variation in the pyroclastic cover affects rainfall-triggered debris flows [10]. Taking the storm water management model (SWMM) model as the simulation platform, Rui Fu et al. established a joint evaluation system for urban drainage and waterlogging prevention [11]. Zhaoyang Zeng et al., Yuheng Yang et al. and Mu Luan et al. combined the SWMM, a 1D model for a drainage system, with LISFLOOD-FP (a 2D hydrodynamic model), ArcGIS and MIKE11, respectively, to simulate rainstorms and waterlogging in typical regions, and proved that the resulting models are capable of simulating the waterlogging and water depth of inundated areas [12-14].

Josep Lluís Ruiz-Bellet et al. applied a multidisciplinary methodology for historical floods reconstruction to 1874 Santa Tecla floods occurred in Catalonia (NE Iberian Peninsula), using both historical information and meteorological data from 20th Century Reanalysis. In light of historical cases [15], Yong Shi discussed the pattern and the spatiotemporal distribution of waterlogging disasters from multiple angles, simulated two disaster scenarios in the construction of hazard model, and applied the scenario simulation to assess the road hazards in Shanghai [16]. The assessment results echoed with the actual data, indicating that the method provides a meaningful reference for government decision-making. Li Weng et al. and Lin Li et al. set up an index system for rainstorm risk evaluation, including the formative factors, post-disaster environment and hazard-affected body, and graded the indices based on relevant data [17-18]; After that, the scholars constructed membership functions to identify the degree of membership between the evaluation factors and evaluation grades, and established a secondary fuzzy comprehensive evaluation model for evaluating the risk of torrential rainstorms.

Wang Li et al. analysed the applicability of satellite rainfall data TRMM 3B42-V7 in Beijing-Tianjin-Hebei region, and, using the TRMM data in 2008-2012, conducted a rapid clustering assessment based on six indices, including slope, the overall GDP, the number of rainstorm days, the number of two-day rainstorms, annual mean number of rainstorms, and annual rainfall in five years [19]. Gayoung Yoo et al. and Qiuling Yao et al. assessed the relative environmental vulnerabilities based on a conceptual diagram of environmental exposure, sensitivity, and adaptive capacity [20-21]. The environmental exposure was measured by the inundation resulted from heavy rainstorm, saltwater intrusion and environmental pollution; the sensitivity was demonstrated by sectors of human and natural systems based on a GIS land cover map; the adaptive capacity was reflected by environmental awareness, policy basis, economic status and infrastructure. Juan Dai et al. selected rainfall, land use, economy and population as indices, and determined their importance by modified AHP and comentropy [22]. Huijuan Pei et al. analysed the spatiotemporal distribution features based on the GIS platform, constructed the index system of the AHP-based regional rainstorm and flood risk assessment, and used the index system to assess the relevant risks in Gansu Province [23].

To sum up, the existing methods for assessing rainstorm waterlogging risks fall into 3 categories: scenario simulation, historical data evaluation and index system assessment. Despite relatively high accuracy, the scenario simulation method is rather complicated by the processing of massive basic data in hydraulic simulation software. Thanks to its simple calculation, the historical data evaluation has been extensively used in agriculture. However, the evaluation accuracy entirely hinges on the precision of historical data. Featuring simple structure, wide application and easy implementation, the index system assessment is constrained by the uncertainty of some indices. Therefore, it is necessary to improve the index system assessment for the urban rainstorm waterlogging risks in this research.

Grey theory and its judgement matrix have been widely used to improve the effect of risk assessment. For example, Junjie Wang et al. designed a new grey incidence model called GDTIM(t) to dynamically analyse the relevant factors of smog weather in southern China’s Jiangsu Province [24]. The analysis results verified that the GDTIM(t) model not only overcomes the drawbacks of index uncertainty, but also stands out as an advantageous problem-solving strategy [25]. Chen Lv et al. extended the interval number judgement matrix by the fraction scale method of 10/10-18/2 and established the computing model for index weights based on the EAHP; On this basis, the scholars divided the risk evaluation index into four grey groups, determined the whitening function for each group, and finalized the improved grey-clustering multi-level comprehensive evaluation method [26]. Chong Li et al. proposed a novel interval-grey-number (IGN) reciprocal-judgment-matrix based the AHP (GRAHP) and built an improved grey variable weight clustering evaluation model [27]. The contributions of the GRAHP are as follows: it offers an index streamlining method based on grey clustering, sets the conversion rule between IGN reciprocal judgment matrix and IGN complementary judgment matrix, creates a grey-AHP algorithm to overcome the constraint of evaluation consistency and perception uncertainty of evaluators, and provides an improved grey variable weight clustering evaluation model for risk level classification [28-29].

In light of the above, grey theory and its judgement matrix has been adopted for various types of risk assessment, save the rainstorm waterlogging risk assessment. As a result, the author relied on the AHP to build a layered evaluation index system, introduced the grey theory to overcome the uncertainty of some indices, and finally created a hierarchical analysis model of grey judgement matrix (Grey-AHP model).

2. Methodology

2.1 AHP

Being an organic combination of quantitative and qualitative analyses, the AHP constructs a fuzzy judgment matrix based on experts’ experience, and applies the matrix to determine the relative importance of each index. The specific steps are as follows.

(1) Construction of the fuzzy judgment matrix

Denote each index in the hierarchical system as C_1, C_2, ..., C_n, and the distributed weight as w_1, w_2, …, w_n. It is possible to construct the judgement matrix A by the importance between indices, and obtain the value of importance through pairwise comparison and the 1~9 scale (Table 1).

The judgment matrix can be obtained from Table 1.

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1m} \\ a_{21} & a_{22} & \cdots & a_{2m} \\ \vdots & \vdots & & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mm} \end{bmatrix} \tag{1}$$

Tab.1. Meaning of the 1~9 Scale of the AHP

Scale	Meaning
1	Index i and Index j are equally important
3	Index i is moderately important than Index j
5	Index i is strongly important than Index j
7	Index i is very strongly important than Index j
9	Index i is extremely strongly important than Index j
2,4,6,8	Intermediate value between adjacent scales
Reciprocal of the above scale	a_{ij} is the value of Index *i* relative to index *j*; a_{ji} is the value of Index *j* relative to index *i*. $a_{ji}=1/a_{ij}$

(2) Consistency check for matrix

If the judgement matrix is inconsistent, the evaluated weights may not be reliable, and mistakes may occur in the assessment. This calls for a consistency check for the matrix.

Firstly, the consistency index CI may be calculated as follows.

$$\mathrm{CI} = \frac{\lambda_{max}-m}{m-1} \tag{2}$$

where, λ_{max} and m are respectively the maximum eigenvalue and the order of judgment matrix A.

Secondly, the mean random consistency index RI should be found. The RI is the arithmetic mean of the CIs calculated randomly by the judgement matrix for over 500 times. Table 2 shows the RIs of the judgement matrix of 1~9 order.

Tab.2. Mean Random Consistency Index Values

Order	1	2	3	4	5	6	7	8	9
RI	0	0	0.52	0.89	1.12	1.26	1.36	1.41	1.46

Finally, the consistency ratio CR can be calculated as below.

$$\mathrm{CR} = \frac{CI}{RI} \tag{3}$$

The judgement matrix is acceptable if CR<0.1; otherwise, the matrix must be corrected before use.

(3) Index weighting

$$w_i = \frac{w_i^*}{\sum_{i=1}^{m} w_i^*} \tag{4}$$

where $w_i^* = \sqrt[m]{M_i}$;$M_i = \prod_{i=1}^{m} a_{ij}$, *i=1, 2, ..., m; j=1, 2, ..., m*

2.2 Grey-AHP Model Based on Grey Judgment Matrix

(1) Definitions

Definition 1: The scope of grey number is known, but the value is unknown. Each grey number is denoted as ⓧ.

Definition 2: The interval grey number refers to any grey number with both the lower bound $\underline{a}$ and the upper bound $\bar{a}$. Each interval grey number is denoted as $ⓧ \in [\underline{a}, \bar{a}]$.

Definition 3: The grey number of ⓧa and ⓧb satisfy the following operations:

$$ⓧa + ⓧb = [\underline{a} + \bar{b}, \bar{a} + \bar{b}] \tag{5}$$

$$ⓧa - ⓧb = [\underline{a} - \bar{b}, \bar{a} - \bar{b}] \tag{6}$$

$$ⓧa + ⓧb = [\min(\underline{ab}, \bar{a}\bar{b}, \underline{a}\bar{b}, \bar{a}\underline{b}), \max(\underline{ab}, \bar{a}\bar{b}, \underline{a}\bar{b}, \bar{a}\underline{b})] \tag{7}$$

$$ⓧa \div ⓧb = ⓧa \times \left[\frac{1}{b}, \frac{1}{b}\right], 0 \neq ⓧb \tag{8}$$

$$\otimes a = \otimes b \Leftrightarrow \underline{a} = \underline{b}, \bar{a} = \bar{b} \tag{9}$$

Definition 4: If $\otimes \in [a, b], a < b, a \neq 0, b \neq 0, ab > 0$, then $\otimes^{-1} \in [\frac{1}{b}, \frac{1}{a}]$.

Definition 5: The grey matrix, denoted as A(⊗), is a matrix of grey elements. The grey number in row i and column j of the grey matrix is expressed as $\otimes_{ij}$ or ⊗(i, j).

Definition 6: Assuming that the grey matrix $D(\otimes)=[\otimes_{ij}]_{m\times n}$, $M(\otimes)=[\otimes_{ij}]_{m\times n}$, then the following operation rule is established:

$$D(\otimes)+M(\otimes)=[\otimes_{ij}+\otimes_{ij}^{'}]_{m\times n} \tag{10}$$

$$D(\otimes)-M(\otimes)=[\otimes_{ij}-\otimes_{ij}^{'}]_{m\times n} \tag{11}$$

$$\otimes\cdot D(\otimes)=[\otimes\cdot\otimes_{ij}]_{m\times n} \tag{12}$$

$$D(\otimes)\cdot M(\otimes)=[\otimes_{ij}^{''}]_{m\times n} \tag{13}$$

(2) Construction of the model

During evaluation, it is sometimes difficult to evaluate indices in accurate numbers. The Grey-AHP model can evaluate values of indices falling in a limited range, and obtain closer-to-reality evaluation results. In this way, the judgement of decision-makers could be reflected more in a more accurate manner.

Suppose $D(\otimes)=[\otimes_{ij}]_{m\times n}$ is a grey matrix, and the corresponding grey weight vector is $w(\otimes) = (w_1(\otimes), w_2(\otimes), \dots, w_n(\otimes))$.

If the matrix is consistent, $\otimes_{ij}=w_i/w_j$ $(i, j=1, 2, ..., n)$, that is, w(⊗)is an eigenvector of D(⊗) belonging to $\lambda=tr(D)$.

Theorem 1: Suppose $D(\otimes)=[\otimes_{ij}]_{m\times n}$ is a grey interval judgment matrix of consistency, and $(\underline{d_{ij}})_{m\times n}$ and $(\overline{d_{ij}})_{m\times n}$ are the normalized eigenvectors with positive component respectively belonging to the maximum eigenvalues $\underline{D}(\otimes)$ and $\overline{D}(\otimes)$. Then, the necessary and sufficient condition for $w(\otimes)=[p\underline{w}, q\overline{w}]=(w_1(\otimes), w_2(\otimes), \dots, w_n(\otimes))^T$ to meet $\otimes_{ij}=w_i/w_j$ $(i, j=1, 2, ..., n)$ is as follows.

$$\Omega=\sum_{j=1}^{n}=\frac{1}{\sum_{i=1}^{n}\overline{d}_{ij}}=\frac{1}{\sum_{j=1}^{n}(\sum_{i=1}^{n}\underline{d}_{ij})^{-1}} \tag{14}$$

Whereas D(ⓧ) is a consistent matrix, the following formulas apply to j=1, 2, ..., n:

$$\underline{w}_i=\underline{d}_{ij}/\sum_{i=1}^{n}\underline{d}_{ij},\quad \overline{w}_i=\overline{d}_{ij}/\sum_{i=1}^{n}\overline{d}_{ij} \tag{15}$$

Whereas $\otimes_{ij}=w_i/w_j$ *(i, j=1, 2, ..., n)*, the following formulas are established:

$$\underline{d}_{ij}=\underline{d}_i/\overline{d}_j,\quad \overline{d}_{ij}=\overline{d}_i/\underline{d}_j \tag{16}$$

Thus, $w_i=[\frac{p}{\sum_{i=1}^{n}\underline{d}_{ij}}\underline{d}_{ij},\frac{q}{\sum_{i=1}^{n}\overline{d}_{ij}}\overline{d}_{ij}]$

$$w_i=[\Omega\cdot\frac{\sum_{i=1}^{n}\overline{d}_{ij}}{\sum_{i=1}^{n}\underline{d}_{ij}}\frac{\underline{d}_i}{\overline{d}_j},\Omega'\cdot\frac{\sum_{i=1}^{n}\underline{d}_{ij}}{\sum_{i=1}^{n}\overline{d}_{ij}}\frac{\overline{d}_i}{\underline{d}_j}] \tag{17}$$

Formula (14) is validated by formula (16).

Considering the expression of Ω, the scores of p and q can be obtained respectively.

$$p=\sqrt{\sum_{j=1}^{n}(\sum_{i=1}^{n}\overline{d}_{ij})^{-1}},\quad q=\sqrt{\sum_{j=1}^{n}(\sum_{i=1}^{n}\underline{d}_{ij})^{-1}} \tag{18}$$

The modelling process of the Grey AHP is illustrated as follows.

(1) Establish the grey judgment matrix;

(2) Calculate the eigenvalue of $(\underline{d_{ij}})_{m\times n}$ and $(\overline{d_{ij}})_{m\times n}$, and find the corresponding eigenvector of $(\underline{w_1},\underline{w_2},\dots,\underline{w_n})^T$and $\overline{(w_1},\overline{w_2},\dots,\overline{w_n})^T$.

(3) Identify the indices of p and q, and normalize the weight vectors.

(4) Rank the indices by weight.

3. Case Study

3.1 Overview

The case study is targeted at the Huangxiao River drainage system in Wuhan, the seat of central China's Hubei Province. In 2015, the mean annual rainfall of the city was 1,427.5mm and the maximum daily rainfall of 197mm was recorded on July 23, 2015. There are 20 relatively independent drainage systems in the downtown, forming a confluence area greater than 1,000km^2. With pump stations running at full capacity, the drainage and pumping capacity stands at 959 m^3/s. The total length of main pipes reaches 1,265 km. The Huangxiao River drainage system has an elevation of 20-24 m, below the mean riverbed elevation of the Yangtze River. The confluence area, drainage and pumping capacity, and total length of main pipes of the drainage system are 53.1km^2, 122.5 m^3/s and 161km, respectively. There are many lakes in the area, such as Huanzi Lake, Xiaonan Lake, Lingjiao Lake, and Tazi Lake. Covering part of the old city, the drainage system is made of old reinforced concrete pipes and concrete pipes. The pump stations suffer from severe deposition of box culverts and aging electromechanical equipment. What is worse, the drainage facilities are damaged by city construction, which drags down the drainage efficiency.

3.2 Construction of the Evaluation Index System

The risk assessment of urban rainstorm waterlogging involves multiple factors on different levels. Hence, the decomposition-coordination principle of large scale systems theory was adopted to decompose the problem into several layers. Then, the multiple factors were streamlined and assigned to different layers. In this research, the factors were categorized into three groups: risk, exposure and vulnerability. According to the actual waterlogging situation in Wuhan and the previous research, the elevation, return period, runoff coefficient, pipe and channel coverage rate, drainage and pumping capacity and river storage capacity are considered as risk factors, population density, building density and economic conditions are considered as exposure factors, and the meteorological hydrology, climate characteristics and receiving waters are considered as vulnerability factors.

The specific index system is shown in Figure 1.

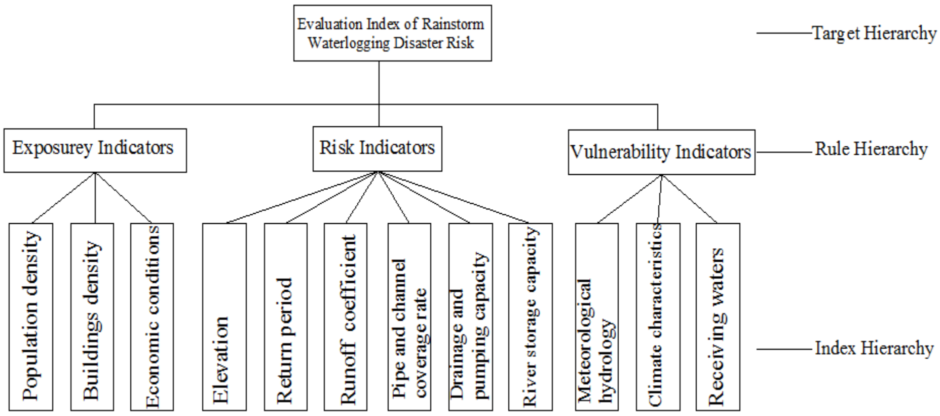

Fig.1. Evaluation Index of Rainstorm Waterlogging Risk

3.3 Weight calculation

Since most of the factors only have an interval value, the grey judgement matrix was chosen for weight calculation. The factors in criterion layer were compared in pairs and the weight was calculated by expert estimation. The results are listed in Table 3.

Tab.3. Pairwise Comparison Results in Criterion Layer

Criterion Layer	Risk	Exposure	Vulnerability	Weight
Risk	[1,1]	[3,4]	[5,7]	[0.52,0.55]
Exposure	[1/4,1/3]	[1,1]	[3,4]	[0.28,0.30]
Vulnerability	[1/7,1/5]	[1/4,1/3]	[1,1]	[0.16,0.20]

The consistency of judgment matrix was tested in the following steps.

First, the grey judgement matrix was split into two parts:

$$M_1 = \begin{bmatrix} 1 & 3 & 5 \\ 1/3 & 1 & 3 \\ 1/5 & 1/3 & 1 \end{bmatrix}, \quad M_2 = \begin{bmatrix} 1 & 4 & 7 \\ 1/4 & 1 & 4 \\ 1/7 & 1/4 & 1 \end{bmatrix}$$

Tab.4. Consistency Check of Judgment Matrix

Judgment Matrix	Criterion Layer	Weight	λ_{max}	RI	CI	CR
	Risk	0.63				
M_1	Exposure	0.25	3.03	0.52	0.015	0.029
	Vulnerability	0.10				
	Risk	0.69				
M_2	Exposure	0.22	3.07	0.52	0.035	0.067
	Vulnerability	0.07				

Tab.5. The Weight of Each Impact Factor

Impact Factors	Scores	Weight	Rank
Population density	[0.12，0.17]	[0.02，0.03]	12
Buildings density	[0.34，0.37]	[0.05，0.07]	9
Economic conditions	[0.46，0.54]	[0.07，0.11]	6
Elevation	[0.20，0.22]	[0.10，0.12]	4
Return period	[0.14，0.15]	[0.07，0.08]	7
Runoff coefficient	[0.21，0.22]	[0.11，0.12]	3
Coverage rate of pipe and channel	[0.10，0.12]	[0.05，0.06]	10
Drainage and pumping capacity	[0.11，0.13]	[0.06，0.07]	8
River storage capacity	[0.21，0.23]	[0.11，0.13]	2
Meteorological hydrology	[0.09，0.12]	[0.03，0.04]	11
Climate characteristics	[0.33，0.34]	[0.09，0.10]	5
Receiving waters	[0.54，0.57]	[0.15，0.17]	1

The results of consistency check on judgment matrices M1 and M2 are listed in Table 4.

As shown in Table 4, the result CR<0.1 fulfils the requirement of consistency, indicating that the grey judgment matrix is consistent.

By means of expert estimation and Grey-AHP model, the 12 impact factors of urban rainstorm waterlogging were compared to calculate weights. The results are presented in Table 5.

3.4 Result Analysis

According to the ranking of impact factors in Table 5, the rainstorm waterlogging in Huangxiao River drainage area is mainly influenced by receiving waters, river storage capacity and runoff coefficient, but little affected by pipe and channel coverage rate, meteorological hydrology and population density. Although there are many lakes in the area, it is difficult for rainwater to flow into them due to poor water quality. The regulation and storage capacity of the open channels and box culverts are severely restrained by the narrow width at key crossroads and severe deposition of culverts. Owing to the limited land and vegetation in the downtown, the runoff coefficient of the drainage system is rather high, and the pipe network covers a wide area. Moreover, the low population density and good meteorological hydrology are attributable to the numerous lakes in the region. The evaluation result is in good agreement with actual situation. Therefore, the focus of waterlogging prevention and mitigation should be laid on the diversion of rainwater and sewage, the control of runoff pollution and the adjustment of lake water regulation and storage. In addition, pipes and channels should be dredged and the main drainage channels should be expanded. As for the runoff coefficient, it should be lowered by controlling land categories, increasing vegetation coverage and implementing permeable concrete pavement.

Conclusions

Essential to disaster prevention and mitigation and sponge city development, the risk assessment of urban rainstorm waterlogging can provide analysts with detailed information on disasters. Facing the uncertainty of some impact indices, the Grey-AHP model was constructed to assess rainstorm waterlogging risk based on grey judgment matrix. The main conclusions are as follows.

(1) The grey judgement matrix was used to calculate the weights and scores of impact factors for assessing rainstorm waterlogging risk. The strategy makes up the defect of existing binary evaluation, and helps to realize continuous and quantitative evaluation.

(2) To overcome index uncertainty, the evaluated index values of the Grey-AHP model fall within a relatively limited scope. The small interval better reflects the intention of decision-makers and leads to closer-to-reality evaluated indices.

(3) Whereas too many indices may complicate the computation and decrease the weighting accuracy, the author will further study the index selection and the importance determination, two key processes in the AHP, seeking to optimize the impact factors of rainstorm waterlogging.

Acknowledgements

The work described in this paper was fully supported by Humanities and Social Sciences Research Projects of Hubei Provincial Department of Education (No 17G044).

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