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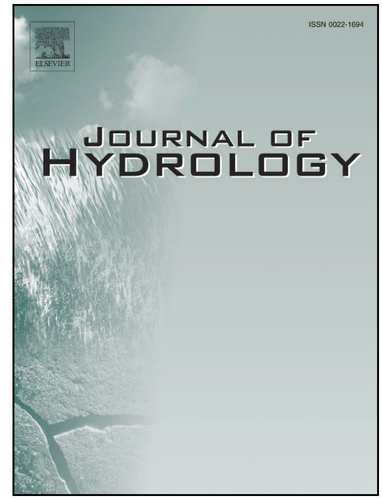

Research papers

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PII:	S0022-1694(21)01194-X
DOI:	https://doi.org/10.1016/j.jhydrol.2021.127144
Reference:	HYDROL 127144
To appear in:	*Journal of Hydrology*
Received Date:	19 July 2020
Revised Date:	25 October 2021
Accepted Date:	27 October 2021

Please cite this article as: Yang, W., Xu, K., Ma, C., Lian, J., Jiang, X., Zhou, Y., Bin, L., A novel multi-objective optimization framework to allocate support funds for flash flood reduction based on multiple vulnerability assessment, *Journal of Hydrology* (2021), doi: https://doi.org/10.1016/j.jhydrol.2021.127144

A novel multi-objective optimization framework to allocate support funds for flash flood reduction based on multiple vulnerability assessment

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Abstract Support funds from national or subnational public spending provide essential assistance for flash floods reduction all around the world. However, how to allocate support funds to different regions with various degrees of disaster is a challenge for decision makers. In this paper, we develop a universal and novel multi-objective framework to solve the problem at multi-space scales. The framework is coupled with the concept of multiple vulnerability and the Fund Allocation Optimization Model (FAOM) developed, taking fully into account the impact of vulnerability on funds allocation. Elite Genetic Algorithm, Technique for Order Preference by Similarity to Ideal Solution and Geographical Detector are applied to solve the FAOM. Based on the case study in Hainan Island, China and the model is compared with the other two fund allocation schemes. Results show that FAOM is able to find a better fund allocation program. As such, it offers a novel approach to solve the problem of funds allocation, considering environmental, social and economic factors. In addition, the further application of the model in progressive recognition and phased support is designed for long-term funding decisions in a particular region, considering the sustainable development of society.

Keywords: Multi-objective, Funds allocation, Flash flood, Vulnerability, Fund Allocation Optimization Model

1 Introduction

Flash flood is one of the most devastating disasters in the world, causing substantial casualties and property losses (Lucía et al. 2018; Liu et al. 2018; Lian et al. 2017; Nielsen et al. 2015; Ahmadalipour and Moradkhani 2019; Diakakis et al. 2020). Serious disaster areas often need to inject a large amount of financial funds from national or subnational public spending for the construction of engineering measures and non-engineering measures, which are conducive to the local disaster prevention and mitigation. The support funds mentioned here focuses on a relatively long-term planning project rather than emergency funding. In China, the government has prepared the Implementation Plan of National Mountain Flood Disaster Prevention Project for three years, and the support funds will be shared by the central and local governments. With increasing tight resources, the total amount of support funds available for different regions is often insufficient, so decision makers should try their best to invest the funds accurately and realize the maximum benefit. To make more scientific decisions, two problems need to be solved. Firstly, identify those areas requiring relative priority support, and secondly, give a more precise funding plan for those areas that need priority support.

About the first problem, some recent literature has examined the determinants of identifying priority support regions. It was often determined by the degree of historical flash floods or the situation of prevention and control tasks in the past (Bubeck et al. 2013; Xu et al. 2018, Nahiduzzaman et al. 2015; Kablan et al. 2017; Karmakar et al. 2010; Huang et al. 2011). Increasingly, more comprehensive concept and factors have been considered to help identify priority support areas. Vulnerability or risk is often used as basis for priority funding area selection. Karim and Noy (2020) examined that flood hazard risk and socio-economic vulnerability are both positively correlated with the sub-district fiscal allocations. Weiler et al. (2018) explored the influence of the vulnerability, good governance and donor interests on priority support regions for adapting to the impacts of climate change. Ahmad and Ma (2020) suggested that gender, membership, farmer size and injured members are the determinants in aid programe through specific case studies.

Over recent years, the term risk and vulnerability have become buzz words in natural hazard. On the definition of risk, IPCC defined it as the product of probability and consequence in 2001(IPCC 2001) and then argued it as the collection of hazard, exposure and vulnerability in 2014(IPCC 2014). The European Environment Agency adopted the flood risk as the product of probability and consequence (UNEP 2004, Shehata and Mizunaga, 2018; Kim and Choi 2011). Some scholars also explained risk as the collection of external risk and internal risk, of which the external risk mainly refers to the potential loss brought by extreme events and the internal risk refers to the decision maker's decision in response to the unexpected situation that may cause greater risk (Roos et al. 2017). On the definition of vulnerability, it has become a popular term in the study of natural disasters and climate change, which refers to disasters, social, economic, population and ecological fields. IPCC defined vulnerability as a function of exposure, sensitivity and adaptive capacity, which is adopted by ETC-CCA &ETCSIA and IUCN (IUCN 2010; Swart et al. 2012; IPCC 2007). Then vulnerability is argued as the tendency of the system to be adversely affected in 2014 (IPCC 2014). Some scholars also emphasized that the definition of vulnerability depends largely on the purpose or the interest of the analysis (Fuchs et al. 2011). Here, we adopted the definition of vulnerability as a set of exposure, sensitivity, and adaptive capacity, which generalize the possible impacts from disasters on regions, considering environmental, social and economic factors synthetically (Chang and Huang 2015; Adger 2006; Andrade and Szlafsztein 2018).

In this paper, the concept of multiple vulnerability from one of our papers which has been published (Yang et al. 2018a) is adopted to identify priority support regions. Multiple vulnerability here was defined as six types (Potential Disaster Loss, Potential Economic Development, Potential Defense Defect, Potential Self-organizing Capability, Potential Disaster Frequency, Potential Resources Waste), considering the relationship between exposure, sensitivity and adaptive capacity, which will give a more comprehensive basis for priority funding area selection.

Multiple vulnerability assessment can identify priority support regions, but how to allocate funds to different regions accurately has always been a challenge, namely, the second problem. Indeed, there are some related researches on resource allocation, most of which are based on the model of emergency dispatch (Balcik et al. 2008; Altay and Green 2006; Anaya-Arenas et al. 2014; Galindo and Batta 2013). Al Theeb and Murray (2017) developed a resource distribution model incorporating features of multi-commodity, multi-depot and multi-period. Huang et al. (2015) presented an integrated decision support model coupling humanitarian principle like lifesaving, human suffering, and fairness, to optimizes resource allocation. Balcik et al. (2008) proposed a mixed integer programming model for optimizing resource allocation in last mile of relief chain.

Based on literature review, we found that previous researches on fund allocation were mostly on account of historical disasters or specific comprehensive concepts like vulnerability or risk (Miller and Vela 2014; Lis and Nickel 2010; Hochrainer-Stigler et al. 2014). Karim and Noy (2020) examined the directly observable determinants of subnational (central to local) public spending allocation for disaster risk reduction and climate change adaptation in Bangladesh. The authors set up a comprehensive indicator system with the primary focus on risk, poverty and politics to explore the determinants of subnational public spending allocation for adaptive disaster risk reduction in the Bangladeshi context. Meanwhile, they established the links between social protection, disaster risk reduction and climate change adaptation and a methodological framework to assess the determinants of public spending allocation, which play an important role in subnational public spending allocation.

However, the research on optimal allocation of disaster prevention funds is still not mature, especially for different space scales. This paper contributes to the literature by offering a novel multi-objective method to determine the allocation of support funds for flash flood reduction in multi-space scales (catchment, town and county). A methodological framework coupling the concept of multiple vulnerability and Fund Allocation Optimization Model (FAOM) is proposed to give the results of optimal allocation of funds from the space scales of catchment, town and county, which helps to maximize the benefit of limited disaster prevention funds and can be generalized.

Heuristic algorithm is a popular approach to solve mathematical model with multiple objectives (Cao et al. 2018). Among them, Genetic Algorithm (GA) has attracted more attention because of its many advantages, including few parameters, good convergence, fine robust and wide extension (Zheng et al. 2015; Su et al. 2016; Soleimani and Kannan 2015). The basic principles of GA are as follows: First, the initial solution of solved problems is generated in a random way, obtaining initial population; Then each individual is evaluated by the fitness function to eliminate the individuals; Next, the individuals with high fitness will be selected to participate in the genetic operation, and the individual set after genetic operation forms the next generation of new population; Then the next round of the new population is carried out. However, in the course of evolution, the adaptive individuals in the current population may be destroyed. To solve the problem, De (1975) put forward the elite selection strategy which saving the best individuals to date in the population evolution and copying them to the next generation with probability 1. The algorithm formed by combining elite retention strategy with GA is called Elitist Genetic Algorithm (EGA). In this study, EGA is designed to solve the FAOM. Then Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is applied to find the final optimal scheme.

Generally, this paper is organized as follows: In Section 2, we introduce in detail the process of building the framework, including multiple vulnerability assessment and the construction of Fund Allocation Optimization Model (FAOM). In Section 3, The framework is applied to Hainan Island and the results of final fund allocation in different catchments, towns and counties are obtained. In Section 4, the rationality and superiority of FAOM has been tested and explained. Meanwhile, the further application of the model is discussed. Finally, we give the conclusions and discuss the limitations of our work.

2 Framework development

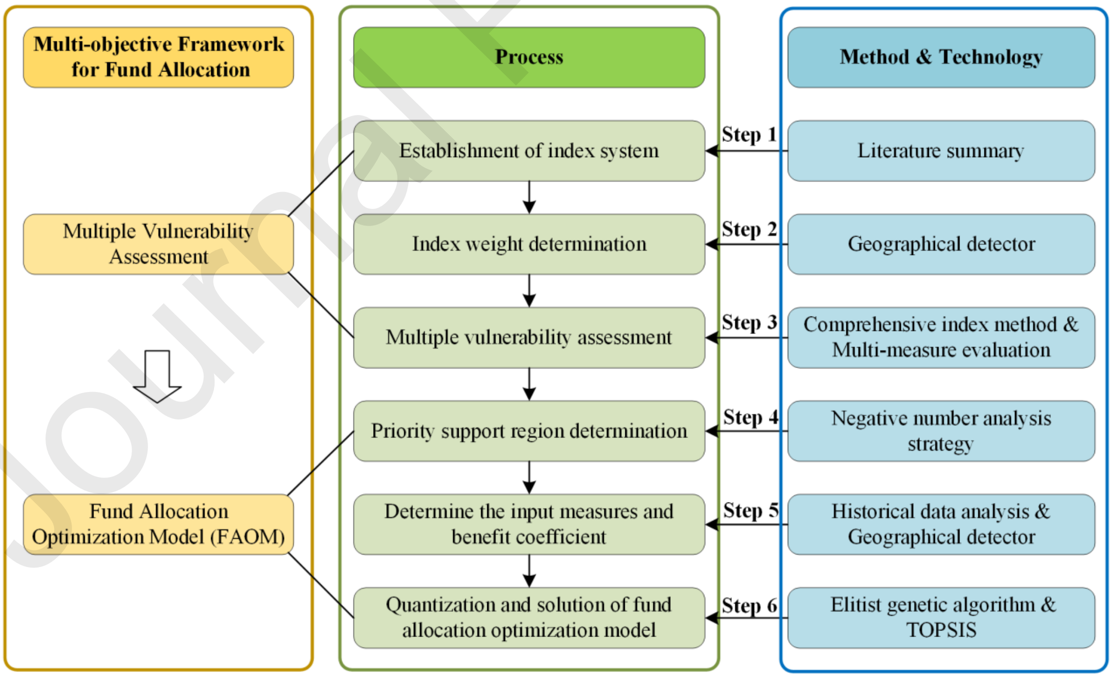

Fig. 1 Novel multi-objective framework of funds allocation for flash flood reduction

To solve the fund allocation problem in different areas, a universal and novel multi-objective framework for flash flood reduction based on the multiple vulnerability assessment and FAOM is developed here. The framework consists of two modules like multiple vulnerability assessment and Fund Allocation Optimization Model, in total of six steps (Fig 1). We will introduce the framework in detail next.

2.1 Multiple vulnerability assessment

2.1.1 Step 1: Establishment of index system

In this study, multiple vulnerability is defined as the interaction of exposure, sensitivity and adaptive capacity (Lian et al. 2017). Exposure in this paper refers to the external pressure (disturbance) and related factors that may affect the magnitude of the pressure (disturbance) (Fuchs et al. 2011). Sensitivity is defined as the degree to which a system is likely to be affected by pressure or disturbance (Chang and Huang 2015). Adaptive capacity is regarded as the ability of a system to enhance its capability to adjust or respond by reducing potential impacts due to flash flood here (Yang et al. 2018a).

Based on literature summary (Carlo 2015; Swart et al. 2012; EEA 2017; Balica et al. 2009,2012; Koutroulis et al. 2018; Bălteanu 2015; Aroca-Jimenez et al. 2017; Khazai et al. 2013; Karagiorgos et al. 2016; Terti et al. 2015; Ahmad and Ma 2020; Mahmood et al. 2016) and the principles of being representative, systematic, measurable, universal and operational, the indicators to characterize the three components of vulnerability have been suggested as Fig 2. Exposure indicators here are suggested as maximum 10-minute rainfall, maximum 1-hour rainfall, maximum 6-hour rainfall, maximum 24-hour rainfall, maximum 6-hour rainfall, annual rainfall, elevation, slope, river density, land use status, soil type and vegetation type. Sensitivity indicators are selected as family economy, housing value, villages number, population density and enterprise density. The adaptive capacity index system includes engineering measures, non-engineering measures and financial state. Specifically, the engineering measures are suggested as reservoir, sluice, culvert, bridge, embankment; Non-engineering measures include automatic monitoring station, simple water level station, simple rainfall station, wireless early warning station; and the gross domestic product (GDP) is regarded as the financial state indicators.

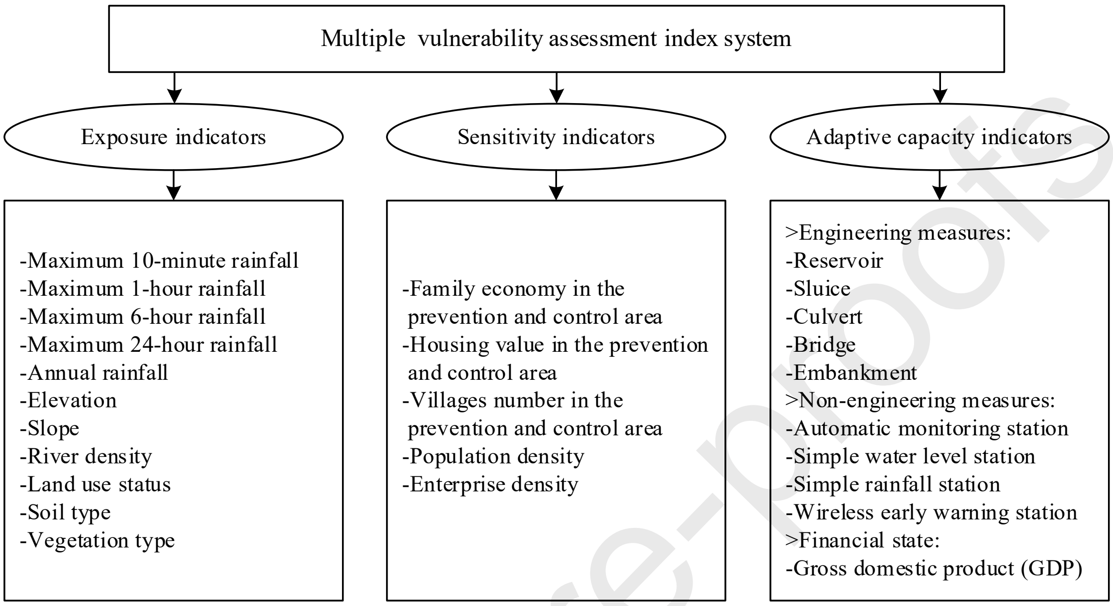

Fig. 2 Multiple vulnerability assessment index system

2.1.2 Step 2: Index weight determination

The common methods of weight determination include subjective weighting (Delphi or Analytic Hierarchy Process), objective weighting (entropy weight method) and comprehensive weighting (Lee et al. 2013; Zeng et al. 2016). All methods have their own advantages and disadvantages. This paper proposes a new weighting method based on geographical detector.

The Geographical detector is a novel statistical method proposed by Wang et al. (2010). The tool's core idea is based on the assumption that if one variable has a significant effect on a dependent variable, then the two variables will have a similar spatial distribution. The geographic detector is able to calculate the extent to which each indicator explains the spatial differentiation of a phenomenon. The greater the interpretation force, the closer the relationship between the index and the phenomenon, and the greater weight of the corresponding index should be. The geographical weighting method makes full use of the spatial distribution relationship between a certain phenomenon and each index, avoiding the former subjectivity and simple objective but may not accord with the actual. A detailed introduction to the principle of geographic detector is as follows:

Define X as a categorical layer, having impacts on the spatial distribution of Y. If the indicator layer X is not a categorical layer, it needs to be classified based on specific principles such as natural breaks class, equal interval class, quantile class and so on. In this study, natural breaks class is adopted. Then the interpretation force (*IF*) from X to Y and the weight of each indicator are measured as:

$$IF = 1 - \frac{1}{N\sigma^2}\sum_{h=1}^{L} N_h \sigma_h^2 \qquad (1)$$

$$\sigma_h^2 = \frac{1}{N_h - 1}\sum_{i=1}^{N_h}\left(N_{h,i} - \overline{N_h}\right)^2 \qquad (2)$$

$$\sigma^2 = \frac{1}{N-1}\sum_{j=1}^{N}\left(N_j - \overline{N}\right)^2 \qquad (3)$$

$$w_j = IF_j / \sum_{j=1}^{m} IF_j \qquad (4)$$

where IF represents the interpretation force from X to the distribution of Y. IF is a value between 0 and 1. The larger the IF, the greater the explanatory power of X to Y. N is the number of samples in the study area; σ^2 means the global variance of Y; N_h represents the samples' number of Y in zone h;$\sigma^2{}_h$ is the variance of Y in the zone h; L is the number of zones; $N_{h,i}$ is the value of Y in *ith* sample of zone h; $\overline{N}_h$ is the average value of Y in zone h; N_j is the value of the *jth* sample unit in the whole study area, $\overline{N}$ is the global average value of Y in entire study area, IF_j is the interpretation force from the *jth* indicator to Y, m is the number of all the indicators selected and w_j is the weight of the *jth* indicator.

2.1.3 Step 3: Multiple vulnerability assessment

Vulnerability is regarded as a concept including three components like exposure, sensitivity and adaptive capacity. They are characterized by a series of indicators, respectively. The specific quantification process is as follows:

$$x_{ij} = \frac{z_{ij} - z_{ij,\min}}{z_{ij,\max} - z_{ij,\min}} (i = 1, ..., m) \quad (5)$$

$$H_i = -k \sum_{j=1}^{n} f_{ij} \ln f_{ij} (i = 1, 2, ...m) \quad (6)$$

$$f_{ij} = \frac{w_j x_{ij}}{\sum_{j=1}^{n} w_j x_{ij}} \quad (7)$$

$$k = \frac{1}{\ln n} \quad (8)$$

$$u_i = 2 - H_i \quad (9)$$

$$EX_i = EX_{u_i} \sum_{j=1}^{n} w_j x_{ij} (i = 1, 2, ..., m; j = 1, 2, ..., n) \quad (10)$$

$$SE_i = SE_{u_i} \sum_{j=1}^{n} w_j x_{ij} (i = 1, 2, ..., m; j = 1, 2, ..., k) \quad (11)$$

$$AC_i = \frac{\sum_{j=1}^{n} w_j x_{ij}}{AC_{u_i}} (i = 1, 2, ..., m; j = 1, 2, ...p) \quad (12)$$

Where z_{ij} is the characterization value of the *jth* index in *ith* unit; x_{ij} is the standardized value of the *jth* index in *ith* unit; $z_{ij,max}$ is the maximum value of the *jth* index in the *ith* unit; $z_{ij,min}$ is the minimum value of the *jth* index in the *ith* unit; H_i is the entropy value of all indicators in the *ith* unit; u_i is inhomogeneity of the *ith* unit proposed by (Yang et al. 2018b); EX_{ui} SE_{ui}, and AC_{ui} is the exposure, sensitivity and adaptive capacity inhomogeneity of the *ith* unit, respectively and EX_i, SE_i and AC_i is exposure, sensitivity and adaptive capacity, respectively.

Here we adopt the concept of multiple vulnerability from one of our papers which has been published (Yang et al. 2018a). Six vulnerability indices, namely, Potential Disaster Loss (PDL), Potential Economic

Development (PED), Potential Defense Defect (PDD), Potential Self-organizing Capability (PSC), Potential Disaster Frequency (PDF) and Potential Resources Waste (PRW), have been developed based on the situation of exposure, sensitivity and adaptive capacity (Table 1). These six vulnerability indices can be classified into positive and negative types for actual disaster prevention and mitigation (Table 1). So far, based on the above formula and the definition of multiple vulnerability, we can identify the multiple vulnerability of all units in study area.

Table 1 Multiple vulnerability and types situation

Situation	Multiple vulnerability	Type
EXi > SEi	Potential Disaster Loss (PDL)	Negative
EXi < SEi	Potential Economic Development (PED)	Positive
SEi > ACi	Potential Defense Defect (PDD)	Negative
SEi < ACi	Potential Self-organizing Capability (PSC)	Positive
EXi > ACi	Potential Disaster Frequency (PDF)	Negative
EXi < ACi	Potential Resources Waste (PRW)	Positive

2.2 Fund Allocation Optimization Model (FAOM) construction

How to allocate support funds to regions with different or the same degree of disaster has always been a challenge for policy makers. Here, a fund allocation optimization model (FAOM) has been developed to solve the problem, according to the results of multiple vulnerability assessment above.

2.2.1 Step 4: Priority support region determination

The degree of disaster should be the criterion to identify priority support regions. Previous definitions of the extent of the disaster may limit to historical flash floods or unilateral natural factors. There is rarely a comprehensive consideration of environmental, social and economic factors, while the multiple vulnerability assessment overcome the above defects. Vulnerability is considered as an important concept to reflect the disaster risk in an area. Based on the results of multiple vulnerability assessment results, the number of negative types of multiple vulnerability of all analysis units ought to be counted first. Then the units with three negative multiple vulnerability will be identified as the priority support regions.

2.2.2 Step 5: Determine the input measures and benefit coefficient

From the concept of multiple vulnerability, PDL and PED reveal the relationship between exposure and sensitivity. Improving PDL to PED is difficult as the exposure reveals the impacts from natural factors, which is always out of our control. On the contrary, it is easier to improve PDD to PSC or PDF to PRW by building related engineering measures and non-engineering measures to increase the local adaptive capacity. Then the input measures can be identified by analyzing the effect of existing disaster prevention measures. Based on the geographical detector, the relationship between the distribution of historical flash floods and the existing measures can be quantized. The results are used to characterize the benefit coefficient of all input measures.

In addition, considering the different effects of various measures on the prevention and control of flash floods and being likely to complement each other, this paper recommends the balanced principle for the investment proportion of all measures. The fund allocation proportion is based on the cost ratio of various measures.

2.2.3 Step 6: Quantization and solution of fund allocation optimization model

To maximize the benefits of investment, a multi-objective fund allocation optimization model (FAOM) has been established. The model consists of two objection function, constraints, decision variable and model solution methods. The details are as follows:

First, in terms of disaster prevention objects, the best decision is to transform the negative type into the positive type as the Table 1 defined, contributing to reduce the number of objects for fund allocation. At the same time, when a region fails to convert all negative types into positive ones, the support fund invested will also produce a certain benefit. After investment, the three negative types of analysis unit may be transformed into the following types: three negative, single positive and double positive. When a single negative type is transformed into a positive type in the same analysis unit, 1/3 of the benefit target is achieved. When the two negative types turn to positive types, the benefit target has been completed 2/3. When the input of funds fails to produce negative type transformation, the corresponding benefit area will also be generated due to the input of funds, but it is less than 1/3 of the target, so we define it as $PAC_i/3Min(EX_i, SE_i)$. Based on the above considerations, the maximum benefit area and the maximum number of positive types are identified as the potential rule of thumb for optimal fund allocation. The two objective functions are defined as follows:

Object function 1: the sum benefit area of all units in study area reaches maximum value. The quantization of benefit area is shown as follows:

$$f(BA) = Max(BA) \qquad (13)$$

$$BA = \sum_{i=1}^{q} \frac{PAC_i * S_i}{3Min(EX_i, SE_i)} + \sum_{i=q+1}^{l} \frac{1}{3} * S_i + \sum_{i=l+1}^{n} \frac{2}{3} * S_i \qquad (14)$$

$$PAC_i = AC_i + IAC_i, i = 1,2,...,n \qquad (15)$$

$$IAC_i = \sum_{j=1}^{k} M_{ij}\omega_j, i = 1,2,...,n; j = 1,2,...,k \qquad (16)$$

$$M_{ij} = \frac{y_{ij} - y_{ij\min}}{y_{ij\max} - y_{ij\min}} \qquad (17)$$

$$y_{ij} = \frac{P_{ij}}{I_j} \qquad (18)$$

Where: *BA* is the sum benefit area of all units in study area; PAC_i is the present adaptive capacity in the *ith* unit; S_i is the area of the *ith* unit; *q* is the number of units with none positive type vulnerability; *l-q* is the number of units with one positive type vulnerability; *n-l* is the number of units with two positive type vulnerability; IAC_i is the added adaptive capacity (Due to the increase of non-engineering measures, the effect of index inhomogeneity on adaptive capacity should be positive, and here we do not take into account it for safety considerations.); M_{ij} is the standardized value of the *jth* measure' number in the *ith* unit; w_j is the benefit coefficient of the *jth* measure; y_{ij} is the *jth* measure' number in the *ith* unit; P_{ij} is the investment of the *jth* measure in the *ith* unit; and I_j is the cost of the *jth* measure.

Object function 2: the sum positive number of vulnerability of all units in study area achieves the maximum value. The specific quantification formulas are as follows:

$$f(Num) = Max(Num) \qquad (19)$$

$$Num = \sum_{i=1}^{n} Num(PAC_i > EX_i or PAC_i > SE_i), i = 1, 2, ..., n \qquad (20)$$

Where: *Num* is the sum positive number of vulnerability of all units in study area; *Max (Num)* is the maximum value of *Num*.

Constraints: The model is subject to constraint like total funds constraints and is shown as follows:

$$P_i = \sum_{j=1}^{k} P_{ij}\ ; \quad P = \sum_{i=1}^{n} P_i \qquad (21)$$

Where: P_i is the investment in the *ith* unit; P_{ij} is the investment of the *jth* measure in the *ith* unit and *P* is the total investment of all the study units.

Decision Variable: Results of allocation funds within each unit.

Model solution: The elitist genetic algorithm (EGA) is applied to solve the model and the Pareto optimal set will be obtained. Then the technique for order preference by similarity to an ideal solution

(TOPSIS) is used to identify the optimal solution. The core thought of TOPSIS is to attempts to choose scheme that simultaneously has the shortest distance from the positive ideal solution and the farthest distance from the negative ideal solution (Mao et al. 2016). It offers a cardinal ranking of the alternatives (Khagram et al. 2003). In this study, TOPSIS is applied to find the optimum solution from Pareto optimal set. The formulas are as follows:

$$a_{i,j} = \frac{H_{i,j}}{\sqrt{\sum_{i=1}^{l} H_{i,j}^2}} \qquad (22)$$

$$A^+ = [a_1^+, a_2^+], A^- = [a_1^-, a_2^-] \qquad (23)$$

$$L_i^+ = \sqrt{\sum_{j=1}^{2} (a_{i,j} - a_j^+)^2} \qquad (24)$$

$$L_i^- = \sqrt{\sum_{j=1}^{2} (a_{i,j} - a_j^-)^2} \qquad (25)$$

$$C_i = \frac{L_i^-}{L_i^+ + L_i^-} \qquad (26)$$

Where: $a_{i,j}$ is the standardized value of the *jth* objective in the *ith* fund allocation scheme; $H_{i,j}$ is the value of the *jth* objective in the *ith* fund allocation scheme; *l* is the number of all fund allocation schemes; A^+ is the maximal ideal solution set; a_1^+ is the maximum value of the first objective in all schemes; a_2^+ is the maximum value of the second objective in all schemes; A^- is the minimum ideal solution set; a_1^- is the minimum value of the first objective in all schemes; a_2^- is the minimum value of the second objective in all schemes; L_i^+ is the distance from the *ith* alternative to the positive ideal solution; L_i^- is the distance from the *ith* alternative to the negative ideal solution; and C_i is the relative closeness from the *ith* scheme to the ideal solution. The scheme with the maximum C_i will be identified as the optimal one.

3 Framework applications

3.1 Study area

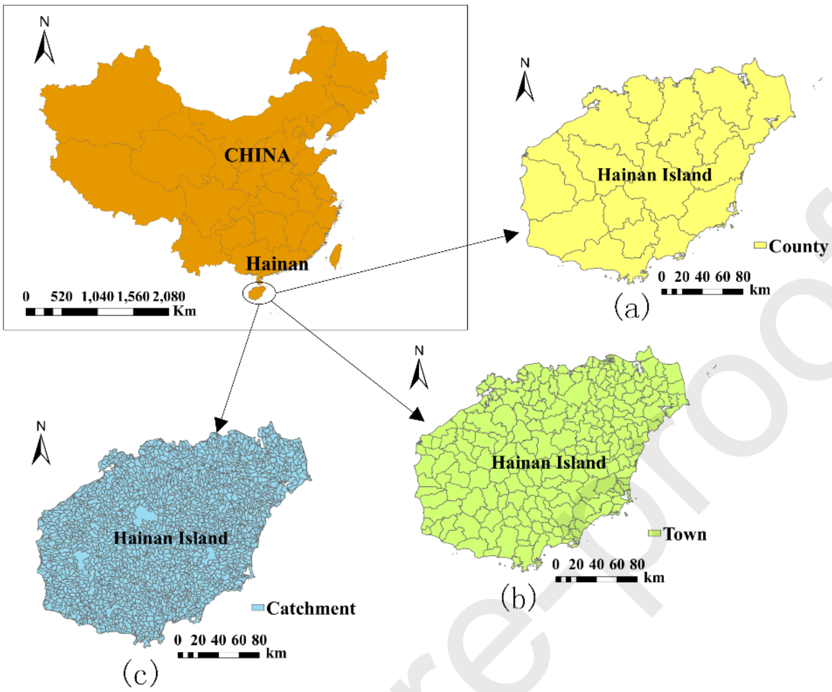

Fig 3 The location map and different spatial scales of the study area

Hainan Island is a tropical island in southern China with an area of 33900 square kilometers and a population of 9.25 million. The location map and the boundary of counties, towns and catchments of Hainan Island are shown in Fig 3. It is located between latitudes 18°38′ and 19°02′ N, and longitudes 109°19′ and 109°44′ E. The overall topography of Hainan Island presents the phenomenon that the middle area is high and the surrounding area is in a low level. It is composed of annular stratiform landforms, and the cascade structure is obvious. The seasonal distribution of precipitation in Hainan Island is very uneven, with dry and wet season. From November to April of each year, there is less rain, accounting for only 10% of the annual rainfall, and drought often occurs in the less rainy season. From May to October each year, there is more rain, with a total rainfall of about 1500 mm, accounting for 70% of the annual rainfall. The main sources of rain are frontal rain, hot thunderstorm and Taiwan storm.

During the rainy season, flash floods often occur and cause numerous casualties and property losses. Therefore, the government has prepared the Implementation Plan of National Mountain Flood Disaster Prevention Project for three years. Then there will be a lot of investment here for the construction of disaster prevention measures, especially non-engineering measures. The allocation of support funds for non-engineering measures in different regions is always a difficult problem for decision makers. Consequently, the framework developed above will be applied to the study area.

3.2 Input data and quantization

Based on the index system developed in the framework, the input data of Hainan Island are collected. The data sources are presented as Table 2 and the quantification and characterization value of each indicator will be described in detail as follows:

All exposure indicators consist of type and numerical variable. The relationship between them and flash floods is difficult to be expressed by single positive or negative correlation. Also, the effect of the numerical variable within different ranges of the same index on flash floods is different. Based on above considerations, the average flash flood intensity is counted in zones classified of all the exposure indicators and they are selected as the characterization value of different exposure indicators. Then the average characterization value of indicators in each catchment can be obtained. To characterize flash flood intensity, a concept of crowding level is defined. The crowding level of flash flood is calculated by the Getis-Ord's Gi* statistic of hot spot analysis in Geographic Information System (GIS) 10.2. Getis-Ord's Gi* can both express the presence of local clustering and indicate the clustering of locations and intensity (Ahmad et al. 2015; Kao et al. 2017). Based on the spatial distribution of recorded flash floods, the average standardized value of z score from Getis-Ord's Gi* can be obtained. Then the value is defined as the crowding level to characterize the flash flood intensity in a catchment. In terms of sensitivity indicators, the average value of family economy, housing value and population density in each catchment is regarded as the characterization value. The crowding levels of villages and enterprises are selected as the characterization value in each catchment. Similarly, about adaptive capacity indicators, all engineering and non-engineering measures are quantized by the crowding levels, basing on the spatial distribution of them. The average GDP is characterized as the characterization value in each catchment.

Table 2 Input data of all indicators

Categories	Indicators	Data sources	Time scales
Exposure	Maximum 10-minute rainfall	HNHWB	1996-2012
	Maximum 1-hour rainfall	HNHWB	1996-2012
	Maximum 6-hour rainfall	HNHWB	1996-2012
	Maximum 24-hour rainfall	HNHWB	1996-2012
	Annual rainfall	HNHWB	1996-2012
	Elevation	FFIEDC	2014
	Slope	FFIEDC	2014
	River density	FFIEDC	2014
	Land use status	RESDC	2010
	Soil type	FFIEDC	2014
	Vegetation type	RESDC	2010
Sensitivity	Family economy	FFIEDC	2014
	Housing value	FFIEDC	2014
	Villages number	FFIEDC	2014

	Population density	RESDC	2010
	Enterprise density	FFIEDC	2014
Adaptive capacity	Reservoir	FFIEDC	By 2014
	Sluice	FFIEDC	By 2014
	Culvert	FFIEDC	By 2014
	Bridge	FFIEDC	By 2014
	Embankment	FFIEDC	By 2014
	Automatic monitoring station	FFIEDC	By 2014
	Simple water level station	FFIEDC	By 2014
	Simple rainfall station	FFIEDC	By 2014
	Wireless early warning station	FFIEDC	By 2014
	GDP	RESDC	2010
Flash flood intensity	Recorded flash floods	FFIEDC	1996-2014

1 Flash Flood Investigation and Evaluation Dataset of China (FFIEDC).

2 Resources and Environmental Sciences Data Center (RESDC), Chinese Academy of Sciences (http://www.resdc.cn).

3 Hainan Province Hydrology and Water Resources Investigation Bureau (HNHWB).

3.3 Results

3.3.1 Multiple vulnerability of flash flood results

Based on the method of multiple vulnerability assessment developed above, the results of exposure, sensitivity, adaptive capacity and the multiple vulnerability are obtained as Fig 4 shows. The overall distribution situation of exposure is that it is high in the northeastern part of the island and low in the southwest. It indicates that flash floods erupt more frequently in the northeastern part of the island. In terms of sensitivity, it is easy to find that the coastal areas own higher sensitivity than that of inland areas. The situation reflects the fact that the economy of coastal areas is more developed than that of inland areas. The adaptive capacity of the whole island is gradually increasing from southwest to northeast, which shows different attentions to flash flood prevention and control from the local people.

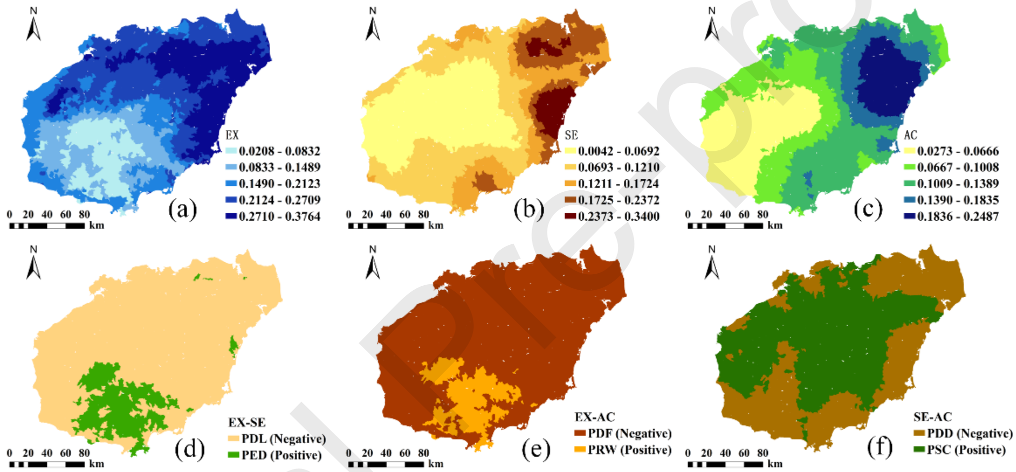

Fig 4 The results of multiple vulnerability in Hainan Island

Then the multiple vulnerability of flash flood can be obtained based on the results of exposure, sensitivity and adaptive capacity. From the relationship between exposure and sensitivity, most areas in Hainan Island are in a negative type as PDL, indicating that most regions own a high potential disaster frequency. Only a few of regions to the south of the island belong to positive type as PED. In terms of the relationship between exposure and adaptive capacity, the spatial distribution of positive and negative types is basically the same as that of exposure and sensitivity. While about sensitivity and adaptive capacity, it shows different spatial distribution laws of the positive and negative types from those of exposure and sensitivity. Coastal areas are negative type as PDD and the inland is positive type. What needs to be emphasized is that all areas in negative type should be paid more attention for disaster prevention and mitigation.

3.3.2 Priority supported catchments determination

To identify the priority supported catchments, it should count the number of negative types vulnerability first. Fig 5a shows the situation of negative types vulnerability in each catchment. It is obvious to find that most catchments in coastal areas contain three negative types vulnerability, which indicates that they should be supported first. Thus, catchments with three negative types are selected as the priority support catchments and are shown in Fig 5b. It is obvious to find that Counties like HK, WC, QH, WN and LD owns the majority catchments for priority support.

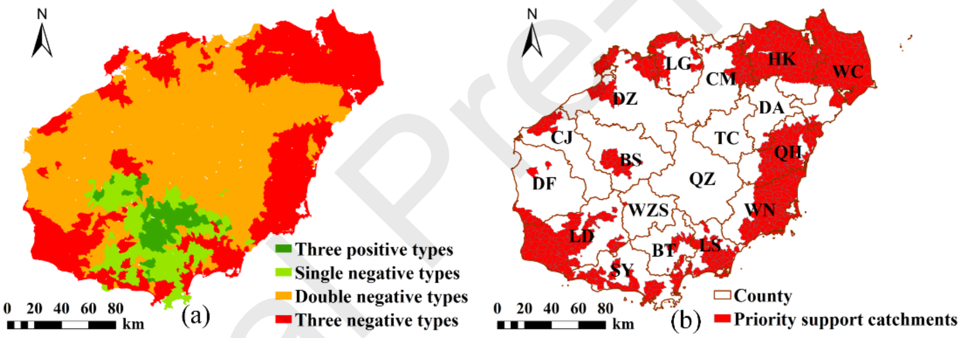

Fig 5 Priority supported catchments identification

3.3.3 Determine the input measures and benefit coefficient of them

Based on the availability of data, this paper only considers the input of non-engineering measures. As a response to flash floods, many non-engineering measures, like simple rainfall station, simple water level station, automatic monitoring station and wireless early warning station, have been implemented in Hainan island. Finished projects in years of 2010 to 2013 are mapped, together with flash floods happened in 2009 to 2010 and 2013 to 2014 (Fig. 6). It is easy to find that the high concentration area of non-engineering measures for 2010-2013 covers almost all of the high-density areas of flash floods in 2009-2010. This shows that the layout of non-engineering measures in 2010-2013 is reasonable. After the implementation of non-engineering measures, the number of flash floods in areas with high intensity of non-engineering is obviously reduced in 2013 to 2014, which further indicates that non-engineering measures play an important role in reducing flash floods. Therefore, the non-engineering measures like simple rainfall station, simple water level station, automatic monitoring station and wireless early warning station should be determined as the planned input measures next year.

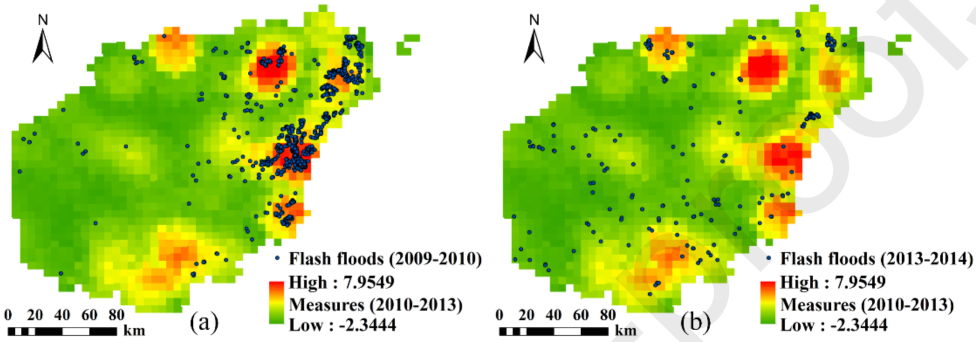

Fig 6 The effect of existing non-engineering measures for flash flood reduction in Hainan Island

Table 3 Benefit coefficient and investment proportion of all measures

Measures	simple rainfall station	simple water level station	automatic monitoring station	wireless early warning station
Benefit coefficient	0.0048	0.0831	0.0333	0.0789
Investment proportion	0.09	0.11	0.55	0.25

Then the benefit coefficients of all measures input are determined by the geographical detector and the investment proportion of all measures are identified based on the cost of them. The results are shown in the table 3. After all data has been prepared, the FAOM can be calculated for finding the optimal solution in next stage.

3.3.4 FAOM results

Statistically, in the past three years, the total support funds from national and subnational in non-engineering measures including monitoring and early warning measures in Hainan has reached 38 million yuan. In general, local government needs to allocate funds according to the current year's budget and disaster prevention requirements. Here, based on the average investment over the past three years, 12 million yuan is expected as the investment to Hainan Island next year. It will be used as a capital entry condition for FAOM.

Table 4 Optimal allocation of funds through TOPSIS

Pareto Optimality	C	Number of active type regions	Benefit area
Case 1	0.74	672	4486
Case 2	0.60	676	4480
Case 3	0.58	675	4480
Case 4	0.26	677	4471

Then the Pareto optimal set can be obtained based on the FAOM. The optimal allocation of funds for priority support regions can be obtained by TOPSIS. The results are shown in Table 4. It is easy to find that the Case 1 has the maximum C value, so the allocation of funds of the case 1 should be selected as the final fund allocation scheme. The two objectives of the scheme like number of active type and the benefit area are 672 and 4486 km^2 , respectively. The spatial distribution of the two objectives are shown in Fig 7. As a result of the investment, the number of negative types in many small watersheds has decreased (Fig 7a). While close to the coastal area, the negative type of some small watersheds in QH, WC and HK still do not decrease, indicating that these areas need more financial input. In terms of benefit area, the disaster prevention ability of each catchment all has been improved in a certain degree, due to the related financial support for disaster prevention. The catchments with high benefit area are mainly concentrated in HK and LD.

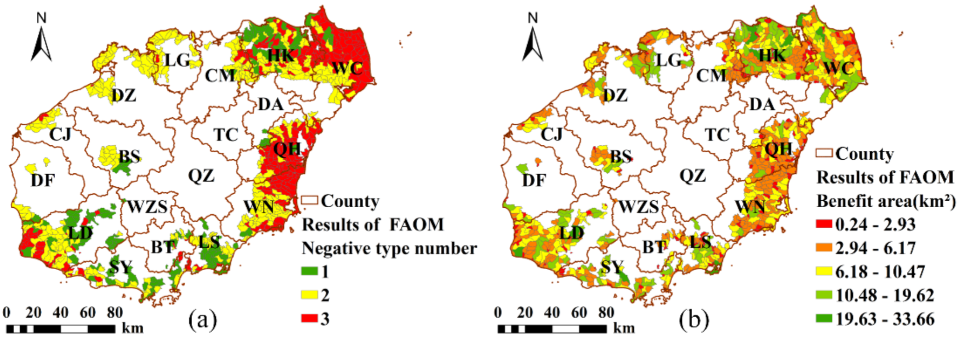

Fig 7 The spatial distribution of two objectives results in catchments

The spatial distribution of fund allocation in catchments is shown in Fig. 8. Based on EGA and TOPSIS, the allocation funds of all catchments for priority support have been obtained. It is not difficult to find that the gap of financial support in different catchments is large. The catchment with minimum investment is only 2400 yuan, while the maximum one has reached 336600 yuan. Such funds allocation results are based on the previous situation of exposure, sensitivity and adaptive capacity of each catchment, which make the allocation more scientific and reasonable.

Generally, the state allocates the money to the provincial units, the provincial units to the municipal and county level units, and then to the town level step by step. Based on the allocation funds on a catchment scale, we can count the total amount of funds allocated to each township and county, which will provide a macro result from meso scale, realizing a scientific decision in real sense. The distribution of funds at the township level is shown in Fig 8b, and that of county level is shown Fig 8c. Since some townships do not have catchment requiring priority support, there is no funding in these towns. The town with the least investment is only 6700 yuan, and the largest is 366500 yuan. On county level, there is a wide gap in allocated funds among all counties. TC and QZ have no supported fund, while HK has been allocated the most funds, reaching 1.93 million. In addition, counties along coast like WC, LD, QH, WN and SY have been allocated more money, as these districts own high vulnerability. These results can give local decision makers necessary references to the allocation of funds from multiple spatial scales, which will be helpful for a more scientific disaster prevention decision.

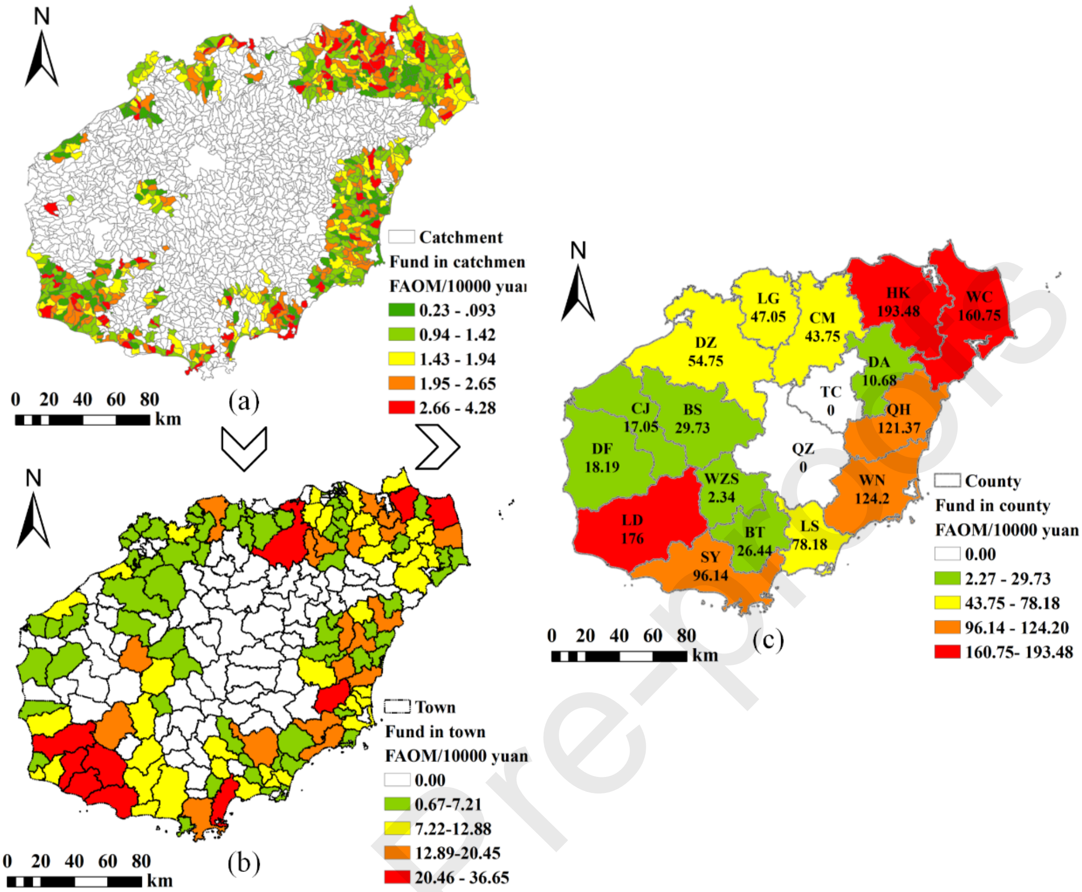

Fig 8 The spatial distribution of funds allocation results in catchments, towns and counties

4 Discussions

In order to show the rationality and superiority of FAOM, two comparison schemes are established here. In general, one area with more flash floods or more control villages (list of villages to be priority controlled by local government) should be supported by more fund for disaster reduction. Therefore, one comparison scheme is based on the history flash floods intensity ratio and the other one is based on the density of villages in control areas. The two schemes are defined as flash flood intensity scheme (FFIS) and control village intensity scheme (CVIS), respectively. In FFIS and CVIS schemes, the quantification of the new adaptive capacity and the ultimate objective function of each catchment is the same as that of the FAOM scheme.

4.1 Model rationality explanation

The situation of funds allocation through FFIS, CVIS and FAOM are different in the catchment, town and county scales. Here, we count the funds allocation from county scale to compare the results of the three schemes. The results are shown in Fig 9. In FFIS, QH is the county obtaining most support funds and it has been nearly 4 million. While, HK, the Capital City of Hainan Province, is the area with the most support funds in both CVIS and FAOM. From this point of view, we can see that the different focus of the three schemes will lead to different funds allocation results. Though different counties are allocated different funds, the trend of funds in all counties are basically consistent among the three schemes. The results show that FAOM has internal consistency with the other two conventional allocation ideas in a certain degree.

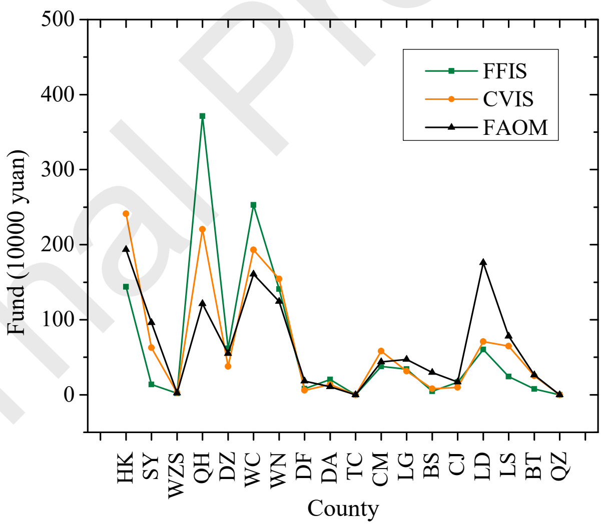

Fig 9 Funds allocation in counties through different schemes

In addition, normally, the state allocates funds generally to provincial units, and then to the municipal and county level. Very few can allocate funds to a catchment scale. FAOM allocates funds from catchment scale to county scale, making more scientific decisions in a real sense.

4.2 Model superiority explanation

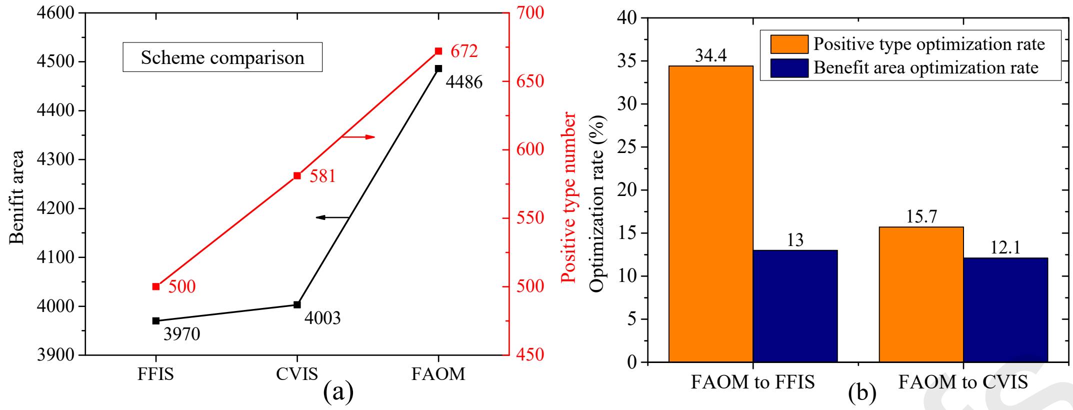

Fig 10 Comparison of objectives of different schemes

Based on the fund allocation results of the three schemes, the two objectives results of them can be obtained and are shown in Fig 10. As the Fig 4a presents, the two objectives of CVIS are both better than those of FFIS. Moreover, the FAOM own maximum positive type number and benefit area meanwhile among the three schemes, which indicates the superiority of FAOM. Further, the optimization rates of FAOM to FFIS and CVIS are shown in Fig 4b. The positive type number optimization rate and benefit area optimization rate from FAOM to FFIS are 34.4% and 13%. Those from FAOM to CVIS are 15.7% and 12.1%. These results fully demonstrate the superiority of FAOM.

Now we give the reasons for that. In the process of solving FAOM, the relationship between the three components of flash flood vulnerability (exposure, sensitivity and adaptive capacity) is fully considered, involving the comprehensive role of various factors (natural, social, anthropic and economical). Consequently, the optimal solution to the allocation of funds can be found through FAOM. While in FFIS, the focus of the funds allocation only is on natural disaster data. Some man-made factors have not been fully considered in the process of resource allocation, including the state of sensitivity and adaptive capacity. Therefore, the allocation of funds for this scheme is not optimal. As for CVIS, the choice of control villages is basically based on the government's rough expert argumentation and then gives a general plan of prevention. In this process, many factors are taken into account, from a more comprehensive perspective than that of FFIS. This also explains why the object results of CVIS scheme are superior to those of FFIS. Of course, it is obvious to find that CVIS is still not as good as FAOM. In summary, The FAOM is superior to the CVIS, and the CVIS is superior to the FFIS.

4.3 Model further application

The further application of the model in progressive recognition and phased support is designed for long-term funding decisions in a particular region, considering the sustainable development of society. The framework is shown in Fig 11. The application process is as follows:

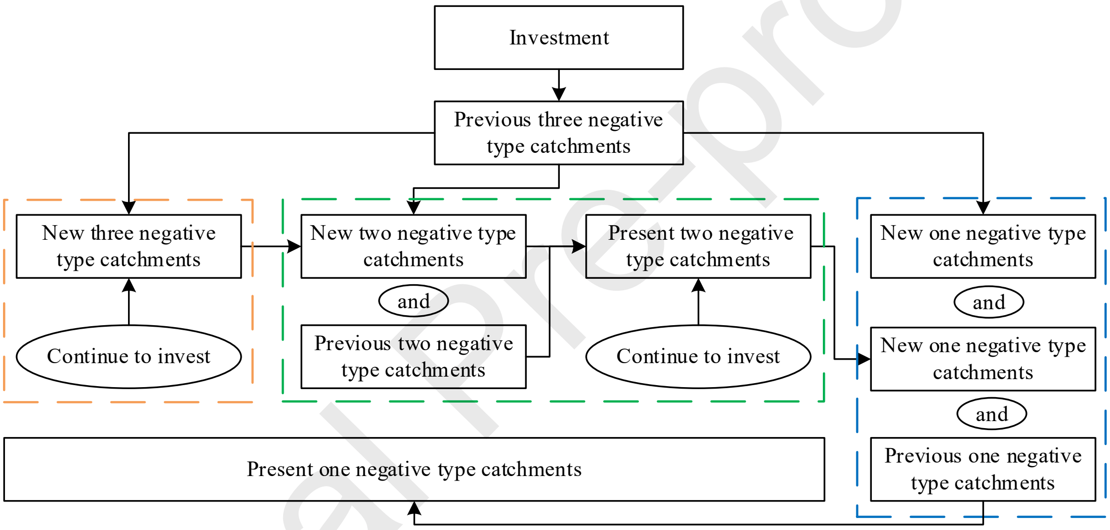

Fig 11 Progressive recognition and phased support framework

The number of catchments with three negative type vulnerability will change after the disbursement of funds in the first stage. These catchments may still stay as three negative type ones, or change to two negative type ones, or directly become one negative type catchments. These catchments staying as three negative types ones need to continue to be invested until they become new two negative type ones. Next, the new two negative type catchments and the previous two negative type catchments will form the present two negative type catchments, which needs to support new funds. Then new one negative type catchments, transferred from the two negative type catchments, and the previous ones will form the present one negative type catchments. The whole process presents a decision idea of progressive recognition and phased support. The application of the framework will provide a practical scheme for disaster prevention and disaster reduction in a region.

4.4 Limitations

Disaster prevention itself is an extremely complex problem, and the allocation of funds for disaster prevention is more difficult to determine. The framework also has its own limitations. Due to limitations of data collection, the index system needs to be further improved for providing a more scientific basis for fund allocation. The indicators will be added in our future work shown as Table 5.

Table 5 Indicators to be added in the future (Karim and Noy (2020)

Categories	Indicators	Description
Exposure	Dangerous building	The number of dilapidated houses
Sensitivity	Poverty rate	The number of people living below the national poverty line
	Enterprise and public institution	The number of Enterprise and public institution
Adaptive capacity	DRR total realized spending	The total (per capita) amount of public fund allocated for disaster risk reduction through disaster risk reduction program.
	GR realized spending	The total (per capita) amount of public fund allocated for disaster risk reduction through gratuitous relief program.
	VGF realized spending	The total (per capita) amount of public fund spent for disaster risk reduction through vulnerable group feeding program.

Note: The acronyms used here represents Disaster Risk Reduction (DRR), Gratuitous Relief (GR) and Vulnerable Group Feeding (VGF) Realized Spending respectively (all in per capita terms).

In addition, the interaction between adjacent regions is not considered in FAOM, although the influence of various factors on the allocation of funds is considered. For example, if two regions are adjacent, what is the impact on one of the regions after the other one increases the disaster prevention measures. Meanwhile, this model only focuses on the specific allocation of funds, while fails to give the location of all kinds of measures in a specific distribution unit. Some improvements to the model require further study in the future.

5 Conclusions

A novel multi-objective framework is developed to allocate support funds to different regions with various degrees of disaster. Key outcomes of the study are as follows:

Firstly, FAOM different from previous resource allocation research is the focus of this study, and multiple vulnerability assessment is incorporated into support funds allocation from multi-space scales. Secondly, an integrated issue concerning support funds allocation is transformed into a multi-objective optimization model, applied to provide decisions for flash floods managers in practice. Thirdly, the whole framework is applied to the fund allocation in Hainan Island and the results has proved that the FAOM has rationality and superiority than conventional fund allocation strategy. Finally, the FAOM can be further applied in disaster prevention and mitigation about the progressive recognition and phased support.

Also, the findings we present have some policy implications in terms of implementing disaster risk reduction program. The progressive recognition and phased support framework developed based on FAOM, will provide a practical policy guidance for disaster prevention and disaster reduction in a region.

In our research, the model developed focuses on the specific allocation of funds, while fails to give the location of all kinds of measures in a specific distribution unit. In addition, the interaction between adjacent regions is not considered in FAOM. We leave the determination of the location of measures and the interaction effect among adjacent regions for future work.

6 Acknowledgements

The research was supported by Natural Science Foundation of Tianjin Education Commission

(2019KJ108, 2019ZD16), State Key Laboratory of Hydraulic Engineering Simulation and Safety Foundation (HESS-2013), the Natural Science Foundation of Tianjin, China (20JCQNJC01540, 18JCZDJC10010, 18JCYBJC22600, 19JCQNJC06900), National Key Research and Development Program of China (2016YFC0401903) and Science Fund for Creative Research Groups of the National Natural Science Foundation of China (51621092). The authors acknowledge the assistance of anonymous reviewers.

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Credit author statement

Weichao Yang: Conceptualization, Methodology, Software, Writing- Original draft preparation.

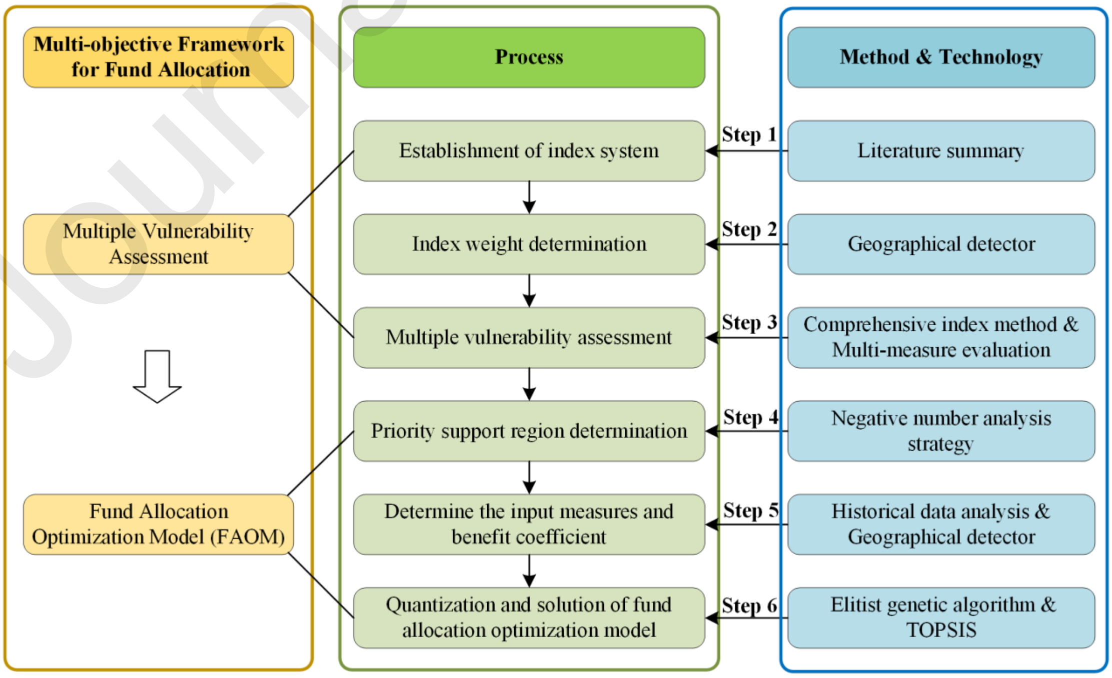
Kui Xu.: Conceptualization, Writing- Reviewing.

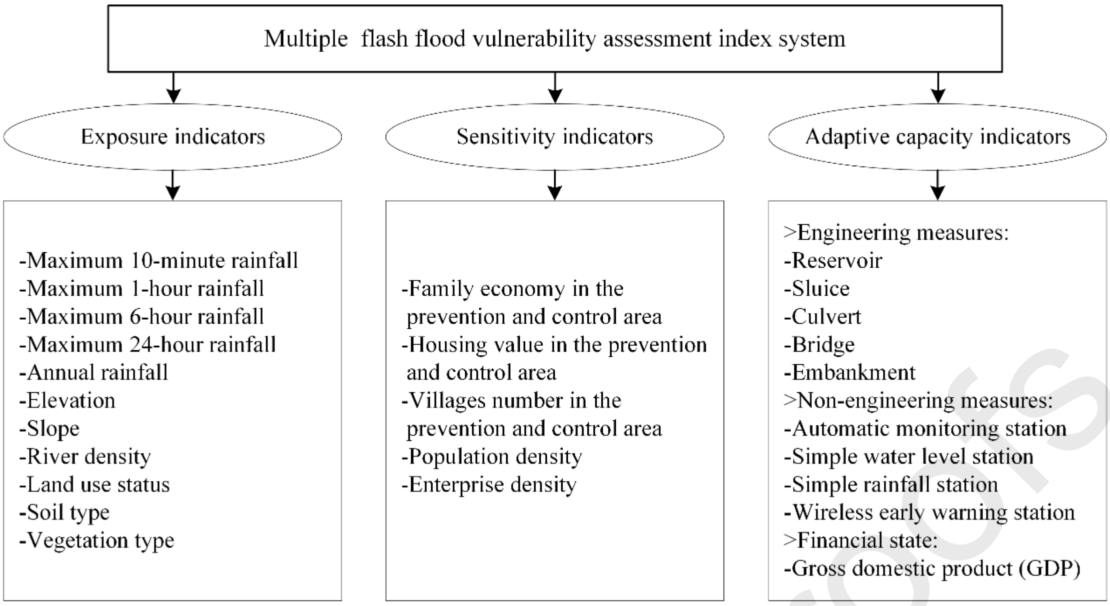
Chao Ma: Writing- Reviewing and Editing.

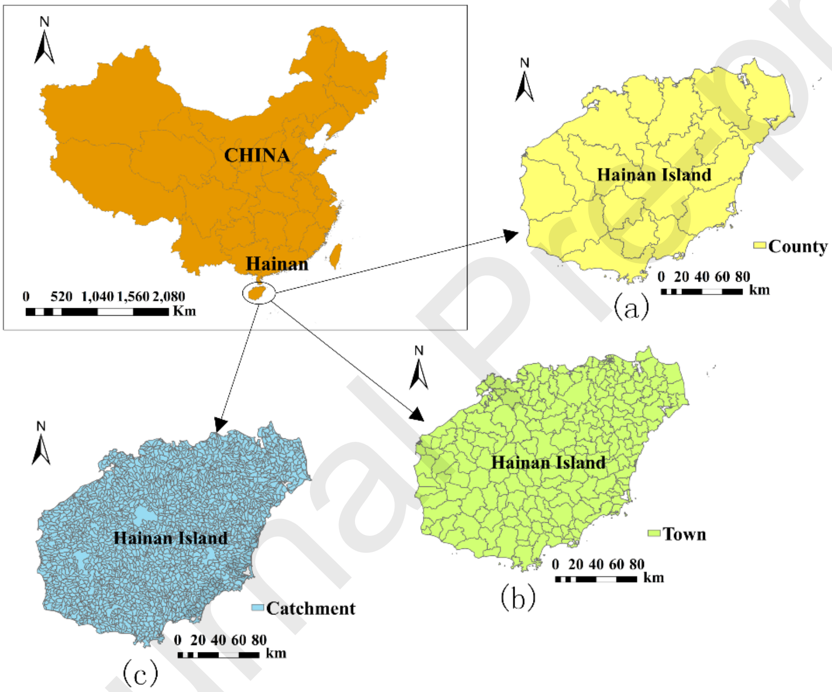
Jijian Lian: Supervision.

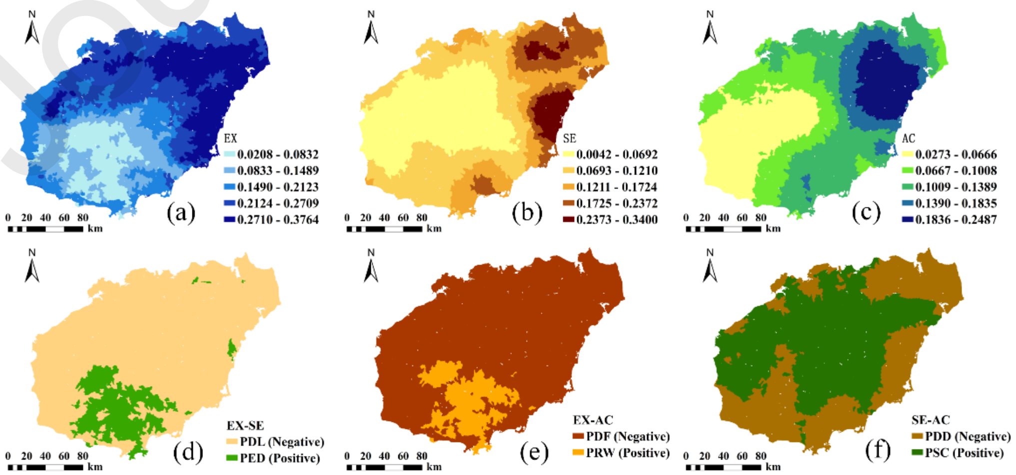
Yadong Zhou: Data curation, Investigation.

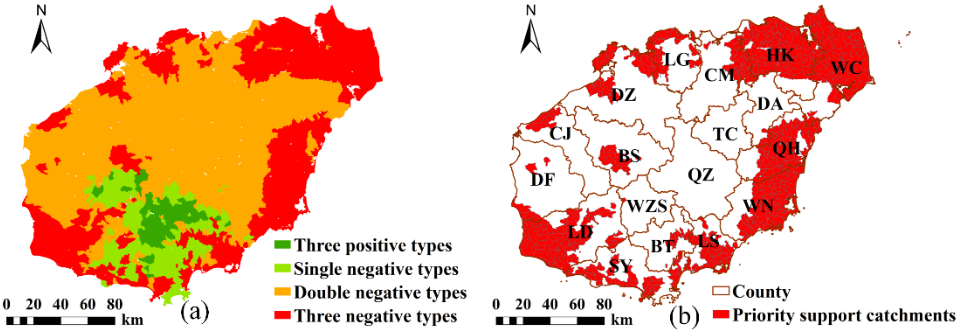
Lingling Bin: Software, Validation.

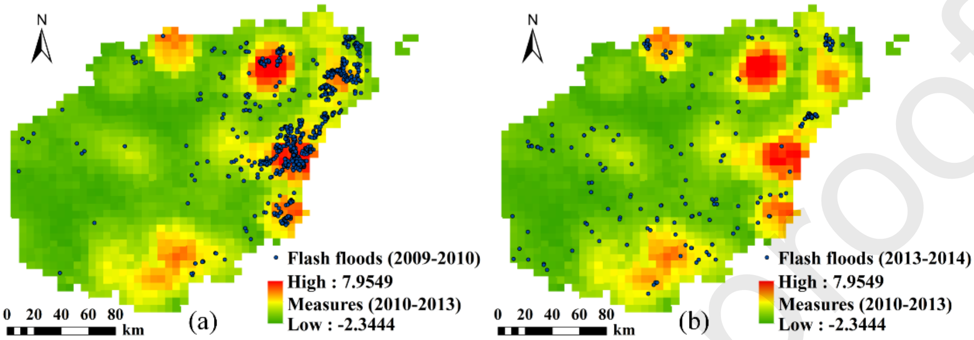


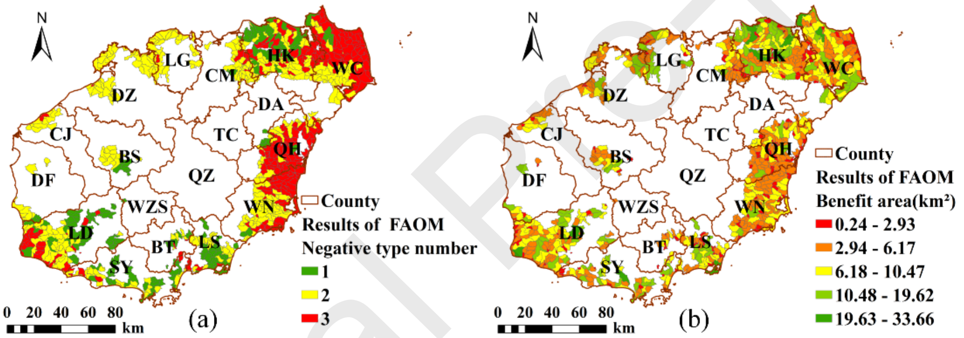

Multiple flash flood vulnerability assessment index system
Exposure indicators
Sensitivity indicators
Adaptive capacity indicators
-Maximum 10-minute rainfall
-Maximum 1-hour rainfall
-Maximum 6-hour rainfall
-Maximum 24-hour rainfall
-Annual rainfall
-Elevation
-Slope
-River density
-Land use status
-Soil type
-Vegetation type
-Family economy in the prevention and control area
-Housing value in the prevention and control area
-Villages number in the prevention and control area
-Population density
-Enterprise density
>Engineering measures:
-Reservoir
-Sluice
-Culvert
-Bridge
-Embankment
>Non-engineering measures:
-Automatic monitoring station
-Simple water level station
-Simple rainfall station
-Wireless early warning station
>Financial state:
-Gross domestic product (GDP)

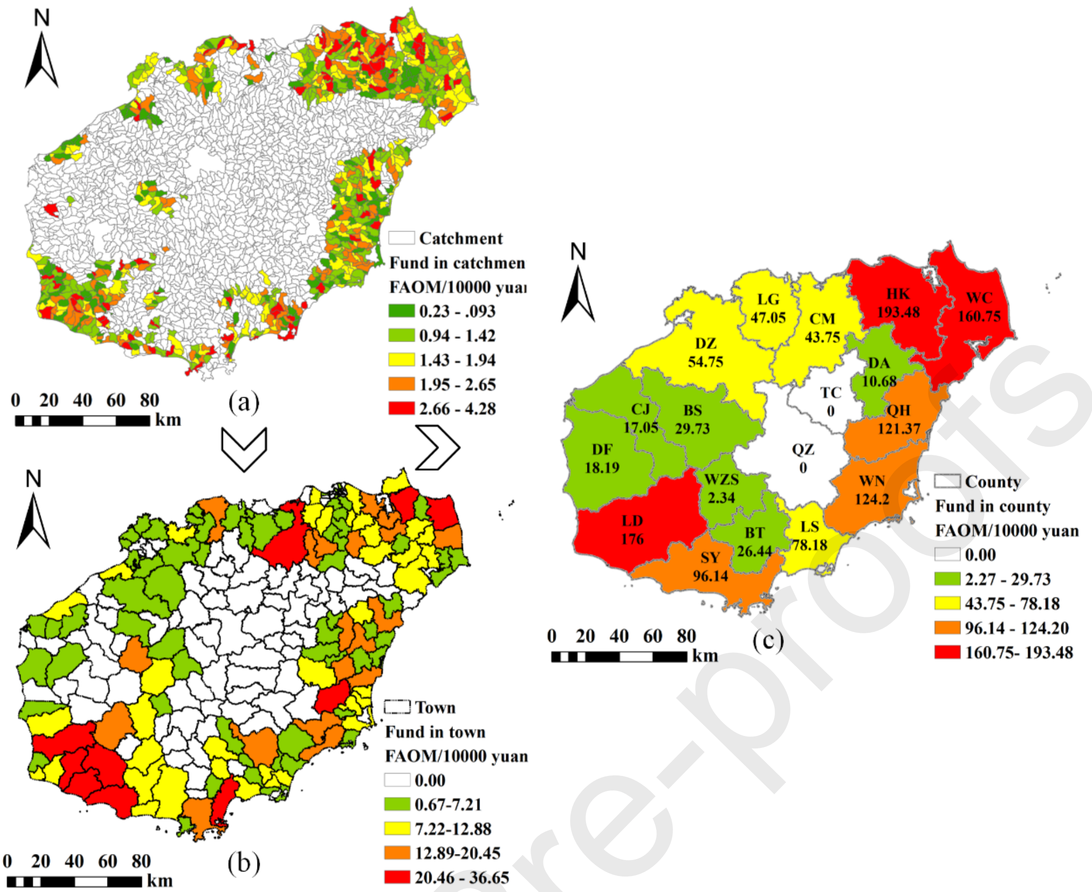

N
CHINA
Hainan
0 520 1,040 1,560 2,080
Km
Hainan Island
County
0 20 40 60 80
km
(a)
Town
(b)
Catchment
(c)

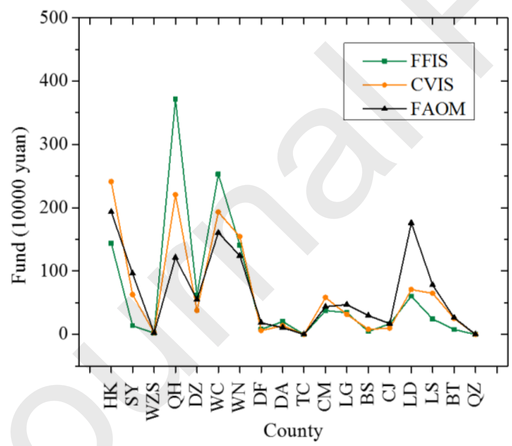

EX
0.0208 - 0.0832
0.0833 - 0.1489
0.1490 - 0.2123
0.2124 - 0.2709
0.2710 - 0.3764
(a)
SE
0.0042 - 0.0692
0.0693 - 0.1210
0.1211 - 0.1724
0.1725 - 0.2372
0.2373 - 0.3400
(b)
AC
0.0273 - 0.0666
0.0667 - 0.1008
0.1009 - 0.1389
0.1390 - 0.1835
0.1836 - 0.2487
(c)
EX-SE
PDL (Negative)
PED (Positive)
(d)
EX-AC
PDF (Negative)
PRW (Positive)
(e)
SE-AC
PDD (Negative)
PSC (Positive)
(f)

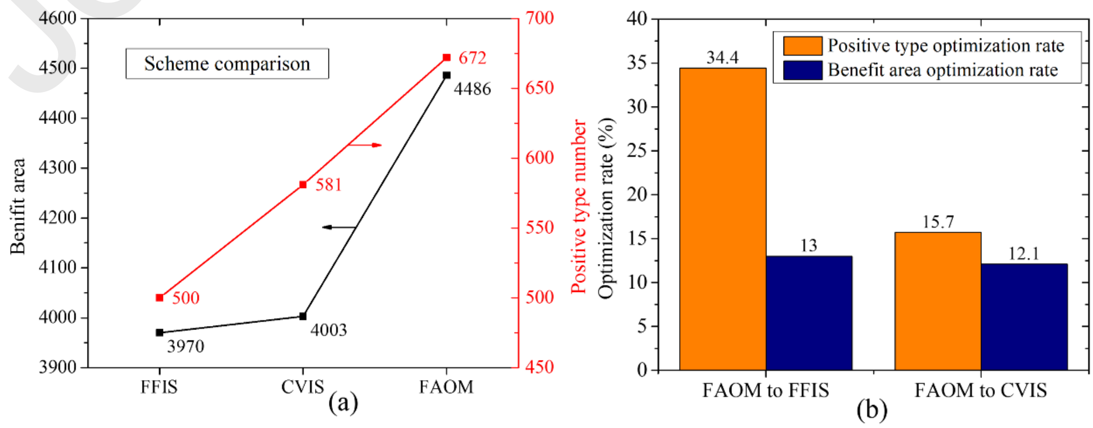

N
Three positive types
Single negative types
Double negative types
Three negative types
0 20 40 60 80
km
(a)
LG
CM
HK
WC
DZ
DA
CJ
TC
QH
BS
DF
QZ
WZS
WN
LD
BT
LS
SY
County
Priority support catchments
(b)


Flash floods (2009-2010)
High : 7.9549
Measures (2010-2013)
Low : -2.3444
(a)
Flash floods (2013-2014)
High : 7.9549
Measures (2010-2013)
Low : -2.3444
(b)


County
Results of FAOM
Negative type number
1
2
3
(a)
County
Results of FAOM
Benefit area(km²)
0.24 - 2.93
2.94 - 6.17
6.18 - 10.47
10.48 - 19.62
19.63 - 33.66
(b)


N
Catchment
Fund in catchmen
FAOM/10000 yuai
0.23 - .093
0.94 - 1.42
1.43 - 1.94
1.95 - 2.65
2.66 - 4.28
0 20 40 60 80
km
(a)
N
Town
Fund in town
FAOM/10000 yuan
0.00
0.67-7.21
7.22-12.88
12.89-20.45
20.46 - 36.65
0 20 40 60 80
km
(b)
N
LG 47.05
CM 43.75
HK 193.48
WC 160.75
DZ 54.75
DA 10.68
TC 0
QH 121.37
CJ 17.05
BS 29.73
DF 18.19
QZ 0
WZS 2.34
WN 124.2
LD 176
BT 26.44
LS 78.18
SY 96.14
County
Fund in county
FAOM/10000 yuan
0.00
2.27 - 29.73
43.75 - 78.18
96.14 - 124.20
160.75- 193.48
0 20 40 60 80
km
(c)


FFIS
CVIS
FAOM
Fund (10000 yuan)
0
100
200
300
400
500
HK SY WZS QH DZ WC WN DF DA TC CM LG BS CJ LD LS BT QZ
County


Scheme comparison
Benifit area
Positive type number
4600
4500
4400
4300
4200
4100
4000
3900
700
650
600
550
500
450
672
581
500
4486
4003
3970
FFIS
CVIS
FAOM
(a)
Positive type optimization rate
Benefit area optimization rate
Optimization rate (%)
0
5
10
15
20
25
30
35
40
34.4
13
15.7
12.1
FAOM to FFIS
FAOM to CVIS
(b)

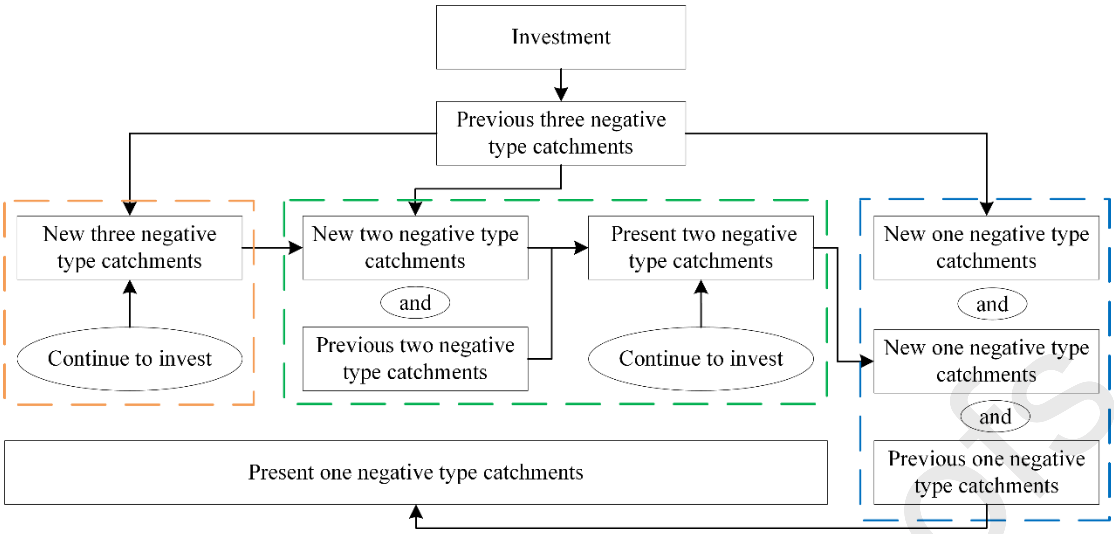


Table 1 Multiple vulnerability and types situation

Situation	Multiple vulnerability	Type
EXi > SEi	Potential Disaster Loss (PDL)	Negative
EXi < SEi	Potential Economic Development (PED)	Positive
SEi > ACi	Potential Defense Defect (PDD)	Negative
SEi < ACi	Potential Self-organizing Capability (PSC)	Positive
EXi > ACi	Potential Disaster Frequency (PDF)	Negative
EXi < ACi	Potential Resources Waste (PRW)	Positive

Table 2 Input data of all indicators

Categories	Indicators	Data sources	Time scales
Exposure	Maximum 10-minute rainfall	HNHWB	1996-2012
	Maximum 1-hour rainfall	HNHWB	1996-2012
	Maximum 6-hour rainfall	HNHWB	1996-2012

	Maximum 24-hour rainfall	HNHWB	1996-2012
	Annual rainfall	HNHWB	1996-2012
	Elevation	FFIEDC	2014
	Slope	FFIEDC	2014
	River density	FFIEDC	2014
	Land use status	RESDC	2010
	Soil type	FFIEDC	2014
	Vegetation type	RESDC	2010
Sensitivity	Family economy	FFIEDC	2014
	Housing value	FFIEDC	2014
	Villages number	FFIEDC	2014
	Population density	RESDC	2010
	Enterprise density	FFIEDC	2014
Adaptive capacity	Reservoir	FFIEDC	By 2014
	Sluice	FFIEDC	By 2014
	Culvert	FFIEDC	By 2014
	Bridge	FFIEDC	By 2014
	Embankment	FFIEDC	By 2014
	Automatic monitoring station	FFIEDC	By 2014
	Simple water level station	FFIEDC	By 2014

	Simple rainfall station	FFIEDC	By 2014
	Wireless early warning station	FFIEDC	By 2014
	GDP	RESDC	2010
Flash flood intensity	Recorded flash floods	FFIEDC	1996-2014

1 Flash Flood Investigation and Evaluation Dataset of China (FFIEDC).

2 Resources and Environmental Sciences Data Center (RESDC), Chinese Academy of Sciences (http://www.resdc.cn).

3 Hainan Province Hydrology and Water Resources Investigation Bureau (HNHWB).

Table 3 Benefit coefficient and investment proportion of all measures

Measures	simple rainfall station	simple water level station	automatic monitoring station	wireless early warning station
Benefit coefficient	0.0048	0.0831	0.0333	0.0789
Investment proportion	0.09	0.11	0.55	0.25

Table 4 Optimal allocation of funds through TOPSIS

Pareto Optimality	C	Number of active type regions	Benefit area
Case 1	0.74	672	4486

Case 2	0.60	676	4480
Case 3	0.58	675	4480
Case 4	0.26	677	4471

Table 5 Indicators to be added in the future (Karim and Noy (2020)

Categories	Indicators	Description
Exposure	Dangerous building	The number of dilapidated houses
Sensitivity	Poverty rate	The number of people living below the national poverty line
	Enterprise and public institution	The number of Enterprise and public institution
Adaptive capacity	DRR total realized spending	The total (per capita) amount of public fund allocated for disaster risk reduction through disaster risk reduction program.
	GR realized spending	The total (per capita) amount of public fund allocated for disaster risk reduction through gratuitous relief program.
	VGF realized spending	The total (per capita) amount of public fund spent for disaster risk reduction through vulnerable group feeding program.

Note: The acronyms used here represents Disaster Risk Reduction (DRR), Gratuitous Relief (GR) and Vulnerable Group Feeding (VGF) Realized Spending respectively (all in per capita terms).

Highlights
- A novel framework of funds allocation for flash flood reduction is proposed;
- The Multiple vulnerability and FAOM are coupled to the framework;
- The rationality and superiority of the framework is evaluated in Hainan Island, China;
- Further application of the framework in progressive recognition is designed.