TELKOMNIKA Telecommunication Computing Electronics and Control
Vol. 22, No. 6, December 2024, pp. 1431~1442
ISSN: 1693-6930, DOI: 10.12928/TELKOMNIKA.v22i6.26272

Flood vulnerability index to aid decision making

Geeta Aggarwal[1], Harita Ahuja[2], Sunita Narang[2], Seema Aggarwal[3]
[1]Department of Computer Science, Pannalal Girdharlal Dayanand Anglo-Vedic College, University of Delhi, Delhi, India
[2]Department of Computer Science, Acharya Narendra Dev College, University of Delhi, Delhi, India
[3]Department of Computer Science, Miranda House College, University of Delhi, Delhi, India

Article Info

Article history:

Received Apr 10, 2024
Revised Aug 20, 2024
Accepted Aug 30, 2024

Keywords:

Decision support system
Disaster management
Flood vulnerability
Multi criteria decision making
Technique for order preference by similarity to ideal solution

ABSTRACT

Floods damage ecosystem of the affected area resulting in destruction, loss of asset and life. The paper proposes a novel k-FVI, (k stands for Kerala and FVI for flood vulnerability index) to aid the decision makers reduce flood vulnerability of 14 districts of Kerala. Instead of usual classification of flood vulnerability indicators under exposure ($\mathbb{E}$), sensitivity ($\mathbb{S}$), and adaptive capacity ($\mathbb{AC}$), k-FVI proposes that, indicators reflecting $\mathbb{S}$ and preparedness ($\mathbb{P}$) govern pre-flood vulnerability, whereas those of $\mathbb{E}$ and rehabilitation ($\mathbb{R}$) affects post-flood vulnerability. The division of $\mathbb{AC}$ indicator into $\mathbb{P}$ and $\mathbb{R}$ indicators and clubbing them into pre-flood and post-flood vulnerability respectively results into reduced errors. The importance of high dimensional flood indicators is realized by measuring the entropy of affected areas. Use of technique for order preference by similarity to ideal solution (TOPSIS) and entropy-based weights to score flood affected area results in formulating robust k-FVI. The paper also compares k-FVI with existing FVIs in literature. It uses data of 2018 Kerala floods and assesses the flood vulnerability of its 14 districts. The results prove that k-FVI is an effective flood vulnerability score estimator. Variant of k-FVI can be used to obtain vulnerability for any other flood prone areas.

Corresponding Author:

Seema Aggarwal
Department of Computer Science, Miranda House College, University of Delhi
Delhi, India
Email: seema.aggarwal@mirandahouse.ac.in

1. INTRODUCTION

Floods are becoming more frequent and intense [1] leading to serious implications like alteration of landscape, eroding of river banks, massive population migrations, and significant decrease in country’s gross domestic product. People living on floodplains have a sense of instability and due to destruction of public services, infrastructure, and lives. The fact that flood-related damages are on the rise is cause for alarm. This study was conducted so that destruction due to floods in future can be minimized by taking appropriate disaster management approaches.

The flood vulnerability index (FVI) combines a number of variables, including land use, hydrology, terrain, climatic patterns, and socioeconomic data, to determine how vulnerable a region is to flooding. FVI is a tool for assessing flood vulnerability at the river basin, drainage area, and urban area scales by classifying distinct components that influence individuals living in flood-prone places. Many people have proposed different methods for computing FVI, some of them have used multi criteria decision making (MCDM) techniques to assign weights to multi-dimensional indicators of FVI viz. exposure ($\mathbb{E}$), sensitivity ($\mathbb{S}$), and adaptive capacity ($\mathbb{AC}$). Several environmental, social, economic, and physical (infrastructure) factors are taken into account while measuring FVI. The entire resource system that is impacted by both human activity and natural circumstances is examined using the environmental vulnerability assessment. When individuals, groups, or civilizations are unable to withstand the damaging consequences of repeated stressors, they are considered socially susceptible. The risks that external shocks pose to the systems of production, distribution, and consumption are referred to as economic vulnerability. Physical vulnerability can be influenced by a number of factors, including population density, town distance, site, architecture, and materials used for housing and essential infrastructure.

The three interrelated area specific indicators around which these four vulnerability components revolve are $\mathbb{E}$, $\mathbb{S}$, and $\mathbb{AC}$. Assets or other elements that may suffer potential losses are referred as $\mathbb{E}$. It is an essential component of risk, but not a sufficient one. $\mathbb{S}$ is the extent to which exposure to climatic variability or geographic risks may have an impact on a system, asset, or species-either negatively or positively. $\mathbb{AC}$ of a system is its property to cope itself to potential damage and consequences of a flood [2].

The authors aim to present a novel technique to calculate reasonable FVI using technique for order preference by similarity to ideal solution (TOPSIS) to further mitigate the adverse impact of floods in future. The FVI score helps decision support system of the affected area to make appropriate strategies. Authors are motivated to generate a novel Kerala-FVI (k-FVI) for minimizing the destruction that may be occur due to future floods in Kerala. It will further support policy makers for risk remediation in order to strengthen decision support system of it's 14 districts. We aim to improve the quality of FVI by using a new classification of indicators instead of the traditional one viz. $\mathbb{E}$, $\mathbb{S}$, and $\mathbb{AC}$. It is pertinent that more the $\mathbb{AC}$, less vulnerable a system is. So, the focus is on improving $\mathbb{AC}$ indicators of flood-stricken areas, keeping in mind to reduce $\mathbb{E}$ and $\mathbb{S}$. The authors suggest that $\mathbb{AC}$ revolves around two subsets of indicators viz. rehabilitation ($\mathbb{R}$) and preparedness ($\mathbb{P}$). The reconstructive measures taken by the authorities on occurrence of floods are known as $\mathbb{R}$ [3]. It intends to gain fast paced recovery and reduce $\mathbb{E}$ in future. Further, activities developed by the authorities to minimize damage to life and property in case of occurrence of floods is called $\mathbb{P}$ [4]. Its goals are to lessen $\mathbb{S}$ and ok the risk of any upcoming floods. The FVI helps to identify high-risk locations and prioritize measures. The authors propose k-FVI that uses a new classification of indicators, such that, indicators reflecting $\mathbb{S}$ and $\mathbb{P}$ govern FVI before the occurrence of floods (pre-flood vulnerability), whereas those of $\mathbb{E}$ and $\mathbb{R}$ affect FVI after the occurrence of floods (post-flood vulnerability). Authors also aim to incorporate TOPSIS on $\mathbb{E}$, $\mathbb{S}$, $\mathbb{R}$, and $\mathbb{P}$ for generating ranks of affected areas. It is pertinent to mention that with the same $\mathbb{E}$ of an area, better the $\mathbb{R}$, lower the post-flood vulnerability of the area. Also, with the constant $\mathbb{S}$ of an area, better the $\mathbb{P}$, lesser the pre-flood vulnerability of the area. The authors have also calculated entropy on affected areas to consider the importance of high dimensional flood indicators of an area. The importance of an area and its TOPSIS score define value of proposed k-FVI. Objectives of the study are: i) detect area specific indicators viz. pre-flood indicators and post-flood indicators; ii) generate ranks based on k-FVI for a decision support system to reduce flood vulnerability in future; and iii) comparative analysis of k-FVI with the existing FVIs, proving better efficacy of k-FVI.

This is how the remainder of the paper is structured. Section 2 discusses related work. The suggested k-FVI's methodology is explained in section 3. Section 4 discusses the experiments and findings in addition to providing an overview of the dataset. Lastly, section 5 provides a conclusion.

2. RELATED WORK

The practice of adequately preparing for and handling disasters is known as disaster management [5], [6]. It aims to prevent or minimize potential losses due to risks, offer disaster victims prompt and appropriate assistance, and guarantee a speedy and efficient recovery. Research by Mortensen *et al.* [7] study the efficacy of disaster risk reduction (DRR) strategies using a worldwide flood risk model in terms of reducing cost and other damages. Floods are a major threat in India [8] with Kerala as one of the most flood-prone state [9]. Kerala experienced a significant flood on August 16, 2018, as a result of abnormally high rainfall during the monsoon season. More than 483 individuals died, and 15 are still unaccounted for. Approximately a million people were evacuated, primarily from "Chengannur", "Pandanad", "Edanad", "Aranmula", "Kozhencherry", "Ayiroor", "Ranni", "Pandalam", "Kuttanad", "Malappuram", "Aluva", "Chalakudy", "Thrissur", "Thiruvalla", "Eraviperoor", "Vallamkulam", "North Paravur", "Chellanam", "Vypin Island", and "Palakka". The state's 14 districts were all placed on "red alert" [10].

The state of being susceptible to injury from exposure to pressures related to environmental and social change, as well as from the lack of ability to adapt, is known as flood vulnerability [11]-[15]. Determining the FVI of a given area is necessary in order to propose risk-reduction strategies. An increasing number of vulnerability assessment techniques and metrics are being updated and enhanced on a regular basis [16]-[18]. Various MCDM techniques have been used to assign weights to multi-dimensional indicators of FVI viz. $\mathbb{E}$, $\mathbb{S}$, and $\mathbb{AC}$ [19], [20]. The studies reveal that TOPSIS, a well-known MCDM technique is more promising in understanding flood vulnerability [21], [22].

FVI is measured by considering several environmental, social, economic, and physical (infrastructure) components [20]. The environmental vulnerability assessment is used to examine the entire resource system that is influenced by natural circumstances and influenced by human activity. People, organizations and civilizations are defined as socially vulnerable when they are unable to endure the negative effects of many stresses. Economic vulnerability refers to the risks posed to the production, distribution and consumption systems by external shocks. Numerous factors, such as population density, distance of a town, site, architecture and materials used for housing and key infrastructure, might affect physical vulnerability [19]. Our solution of k-FVI uses new classification of indicators, entropy measurement and TOPSIS to compute ranks of affected areas.

3. METHOD

This paper proposes a novel FVI variant, named k-FVI for predicting vulnerability of flood-stricken districts of Kerala. Though k-FVI is designed for Kerala state, but the variant can be readily used to obtain vulnerability for any other flood prone area. The pseudocode for k-FVI is depicted in Figure 1. It takes two inputs viz. set of areas ($\mathbb{A}$) whose vulnerability index is to be calculated and the set of indicators ($\mathbb{FI}$) which affects the area's flood vulnerability. The corresponding values of indicators in each area are stored as a two-dimensional MCDM matrix. The output of the pseudocode is the vulnerability index ($\mathbb{V}$) which is based on multiple indicators in $\mathbb{FI}$ and is computed for each area in $\mathbb{A}$ making it a relevant MCDM problem.

Input:

- $\mathbb{A}$ **:** Set of areas affected by flood
- $\mathbb{FI}$ **:** Set of flood indicators for the areas

Output:

- $\mathbb{V}$ **:** *k-FVI* for each area in $\mathbb{A}$

Input Phase: ***FID*** forms two indicator subsets from $\mathbb{FI}$

$\mathbb{FI}_{Pre} \leftarrow \mathbb{P} \cup \mathbb{S}$

$\mathbb{FI}_{Post} \leftarrow \mathbb{E} \cup \mathbb{R}$

// $\mathbb{P}$ and $\mathbb{S}$ are set of indicators reflecting preparedness and sensitivity of an area before floods respectively

// $\mathbb{E}$ and $\mathbb{R}$ are set of indicators reflecting exposure and rehabilitation of an area after floods respectively

// $\mathbb{FI}_{Pre}$ and $\mathbb{FI}_{Post}$ are set of pre-flood and post-flood indicators respectively

Process Phase:

- ***SS*** sub unit of ***FVC*** calculates TOPSIS score for each area $\in \mathbb{A}$

$S_P \leftarrow Topsis(\mathbb{A}, \mathbb{P})$; $S_S \leftarrow Topsis(\mathbb{A}, \mathbb{S})$

$S_E \leftarrow Topsis(\mathbb{A}, \mathbb{E})$; $S_R \leftarrow Topsis(\mathbb{A}, \mathbb{R})$

//S_P and S_S are scores obtained for areas considering preparedness and sensitivity indicators respectively

//S_E and S_R are scores obtained for areas considering exposure and rehabilitation indicators respectively

$Scr_{pre} \leftarrow S_S - S_P$

$Scr_{post} \leftarrow S_E - S_R$

// Scr_{pre} and Scr_{post} are subtracted scores before and after the floods respectively

- ***AA*** sub unit of ***FVC*** calculates importance of each area $\in \mathbb{A}$ before and after the flood

$Imp_{pre} \leftarrow 1 - nH(\mathbb{A}, \mathbb{FI}_{Pre})$;

$Imp_{post} \leftarrow 1 - nH(\mathbb{A}, \mathbb{FI}_{Post})$

// $nH(\mathbb{A}, \mathbb{FI}_{Pre})$ and $nH(\mathbb{A}, \mathbb{FI}_{Post})$ are normalized entropy of an area before the occurrence of floods and after the occurrence of floods respectively and Imp_{pre} and Imp_{post} are importance of area before and after the floods respectively

Output Phase: ***FVB*** calculates FVB scores for each area $\in \mathbb{A}$ before and after floods respectively

$FVB_{Pre} \leftarrow Imp_{pre} \times Scr_{pre}$

$FVB_{Post} \leftarrow Imp_{post} \times Scr_{post}$

$k\_FVI \leftarrow FVB_{Pre} \times FVB_{Post}$

// FVB_{Pre} *and* FVB_{Post} are FVB scores of areas before and after the floods respectively

$\mathbb{V} \leftarrow Sort(\mathbb{A}, k\_FVI)$

Figure 1. Pseudocode for novel k-FVI to calculate vulnerability index

The proposed k-FVI has 3 units viz. Flood indicator detector (FID), flood vulnerability calculator (FVC), and flood vulnerability binder (FVB). The unit FID at input phase categorizes $\mathbb{FI}$ into two indicator subsets signifying pre-flood indicators ($\mathbb{FI}_{\mathrm{Pre}}$) and post-flood indicators ($\mathbb{FI}_{\mathrm{Post}}$). FVC at processing phase obtains TOPSIS score along with entropy of each area in $\mathbb{A}$. Finally, FVB at output phase calculates k-FVI after binding the information gathered by FVC. The working of units at each phase is briefly discussed in the following subsections.

3.1. Flood indicator detector at input phase

In the Input phase, the unit FID takes $\mathbb{FI}$ as input which is a set of flood indicators for the affected areas. It categorizes the input indicators in $\mathbb{FI}_{Pre}$ and $\mathbb{FI}_{Post}$ respectively. These sets serve as input for the process phase. As per the literature survey, researchers have grouped the indicators in $\mathbb{FI}$ into three categories viz. $\mathbb{E}$, $\mathbb{S}$, and $\mathbb{AC}$. To quantify the accountability of towns to flooding from current storms as well as storms under hypothetical future sea level scenarios, $\mathbb{V}$ has been established using (1) [17]. Artificial neural networks, hydrodynamic models, and geospatial methodologies have been employed to provide a depiction of food susceptibility using (2) [19]. Researchers have also used 25 indicators for calculating $\mathbb{V}$ using (3) [18]. For each state and UT, the susceptibility to COVID-19 instances and deaths has also been computed using (4) [20].

$$\mathbb{V} = \mathbb{E} * \mathbb{S} * \mathbb{AC} \quad (1)$$

$$\mathbb{V} = \mathbb{E} + \mathbb{S} - \mathbb{AC} \quad (2)$$

$$\mathbb{V} = (\mathbb{E} * \mathbb{S})/\mathbb{AC} \quad (3)$$

$$\mathbb{V} = (\mathbb{E} - \mathbb{AC}) * \mathbb{S} \quad (4)$$

The literature survey suggests that the researchers have tried to evolve $\mathbb{V}$ by restricting themselves to revolve around these three types of indicators ($\mathbb{E}$, $\mathbb{S}$, and $\mathbb{AC}$). The authors of this paper observed that $\mathbb{AC}$ indicator consists of mainly two sub indicators $\mathbb{P}$ and $\mathbb{R}$. The action plan that the authorities construct to counter the damage to life and property in case of occurrence of floods amounts to $\mathbb{P}$. It includes steps like implementing methods for safety and shelter of people, educating them thereby increasing the literacy level, and increasing the number of stations. Thus, $\mathbb{P}$ falls under the category of $\mathbb{FI}_{Pre}$. On the other hand, $\mathbb{R}$ consists of reconstructive measures taken by the authorities to restore the life to normalcy. $\mathbb{R}$ would depend on the extent to which the disaster has struck thus affecting the total cost of search, rescue, and repair. Thus, it falls under the category of $\mathbb{FI}_{Post}$. Also, authors are of the view that by definition, $\mathbb{E}$ is evident as part of $\mathbb{FI}_{Post}$ and $\mathbb{S}$ is evident as part of $\mathbb{FI}_{Pre}$. Keeping this in mind, authors suggest a novel categorization of $\mathbb{FI}$ into two new subsets viz. $\mathbb{FI}_{Pre}$ and $\mathbb{FI}_{Post}$. $\mathbb{E}$ comprises of availability of healthcare facilities and amount of damage on basic infrastructure facilities. $\mathbb{S}$ includes activities like building dams' reservoirs, decreasing both rural and urban unemployment rate. Thus, $\mathbb{FI}_{Pre}$ include those indicators which reflect the $\mathbb{P}$ and $\mathbb{S}$ of an area before occurrence of floods respectively as shown in (5). On the other hand, $\mathbb{FI}_{Post}$ is the set of indicators which reflect $\mathbb{E}$ and $\mathbb{R}$ of an area after occurrence of floods respectively as shown in (6). To the best of our knowledge such categorization also has not been suggested in literature so far. The authors claim that such division into pre and post indicators will certainly make information depicted by $\mathbb{V}$ clearer and more understandable which will help policy makers to take appropriate action.

$$\mathbb{FI}_{Pre} \leftarrow \mathbb{P} \cup \mathbb{S} \quad (5)$$

$$\mathbb{FI}_{Post} \leftarrow \mathbb{E} \cup \mathbb{R} \quad (6)$$

3.2. Flood vulnerability calculator at process phase

In the process phase, FVC unit takes $\mathbb{FI}_{Pre}$ and $\mathbb{FI}_{Post}$ as input for the flood affected areas. It has two sub units score subtractor (SS) and area analyzer (AA). The SS sub unit of FVC calculates TOPSIS score for each area. As per the literature survey, researchers have applied TOPSIS, a MCDM tool, for obtaining vulnerability index [23]. TOPSIS removes doubt and promotes a more transparent and objective decision-making process by evaluating options based on a variety of criteria thus eliminating subjective judgments and human biases [16]. Its use in generating flood risk maps with the aim to detect flood vulnerable areas of Navsari City in Gujrat, India have proved to be more rational and efficient [21]. Further, when compared to analytical hierarchy process (AHP), which is another popular MCDM tool, compared to the AHP approach, the TOPSIS approach assessed flood risk exposure more accurately [21]. In order to visually grasp the Indian district of Koch, Bihar, flood susceptibility mapping, TOPSIS tool ranked areas on basis of 21 criteria [24]. When compared with another MCDM tool, *viekriterijumsko kompromisno rangiranje* (VIKOR), TOPSIS have produced an excellent result and are strongly advised for determining flood vulnerability in the eastern Indian Sub-Himalayan foothills region, which is a region that experiences frequent flooding [25]. Based on this literature survey, authors have used TOPSIS in FVC unit.

In particular, the SS sub unit calculates S_P and S_S which are TOPSIS scores obtained for areas considering $\mathbb{P}$ and $\mathbb{S}$ indicators respectively using (7). It also calculates S_E and S_R TOPSIS scores which are obtained for all areas considering $\mathbb{E}$ and $\mathbb{R}$ indicators respectively using (8). Finally, the TOPSIS scores Scr_{pre} and Scr_{post} for pre-flood and post-flood indicators are calculated respectively. Initially Scr_{pre} is calculated by subtracting TOPSIS score on $\mathbb{P}$ from TOPSIS score on $\mathbb{S}$ using (9). Likewise, SS sub unit further calculates Scr_{post} using (10) by subtracting TOPSIS score on $\mathbb{R}$ from TOPSIS score on exposure. Thus, the novel SS sub unit generates much more transparent values of Scr_{pre} and Scr_{post} and has not been attempted by any other existing algorithm. It is pertinent to mention that with the same $\mathbb{E}$ of an area, better the $\mathbb{R}$, lower the post-flood vulnerability of the area. Also, with the constant $\mathbb{S}$ of an area, better the $\mathbb{P}$, lesser the pre-flood vulnerability of the area.

$$S_P \leftarrow Topsis(\mathbb{A}, \mathbb{P}); S_S \leftarrow Topsis(\mathbb{A}, \mathbb{S}) \tag{7}$$

$$S_E \leftarrow Topsis(\mathbb{A}, \mathbb{E}); S_R \leftarrow Topsis(\mathbb{A}, \mathbb{R}) \tag{8}$$

$$Scr_{pre} \leftarrow S_S - S_P \tag{9}$$

$$Scr_{post} \leftarrow S_E - S_R \tag{10}$$

It is pertinent to mention that the ranking of flood-stricken areas generated by SS sub unit is robust. But it lacks to incorporate quality information by focusing on flood indicators, there by planning for increased $\mathbb{P}$ and $\mathbb{R}$ of the flood-stricken areas in the future. It is of utmost necessity to incorporate the AA sub unit of FVC which uses Shannon entropy to determine areas that are more influential in flood occurrence [26], [27]. Entropy of an area (system) represents its instability (disorder, uncertainties) which depict main factors among available factors of an event [28] responsible for occurrence of an event.

Literature study suggests use of Shannon entropy model for accurately assessing potential flood-prone regions. It has been used to quantify the information found in specific variables of a region, where higher weight factors contribute more to flood hazard than lower weight factors, in order to assess the importance of factors in triggering floods [29]. Lian *et al.* [30] assessed the risk of flash floods using the material flow technique. The investigation determined how vulnerable each nation in China's Yangtze River Delta was to different threats [31], [32]. Using the entropy model, another research was able to identify places in the Madarsoo watershed in Iran that were susceptible to flooding [28]. The application of entropy has been useful in providing an objective assessment of the spatial pattern of flood risk in Peninsular Malaysia [33]. Shannon's entropy is used to map coastal areas that are susceptible to flooding and to forecast the contribution of many elements to floods in the Sultanate of Oman's Governorate of Muscat [34]. The quantitative inhomogeneity among $\mathbb{E}$, $\mathbb{S}$, and $\mathbb{AC}$ indicators influence flood vulnerability assessment and is evaluated by applying the Shannon entropy method [9]. The weight of an area given by traditional FVC is impacted by expert knowledge and human judgement [35]. This shortcoming can be avoided by AA sub unit which uses an entropy-based weighting method for flood-stricken areas [36]. Thus, authors of this paper chose to use entropy in AA sub unit to calculate the importance of each area before the floods (Imp_{pre}) and after the floods (Imp_{post}) respectively using (11) and (12):

$$Imp_{pre} \leftarrow 1 - nH(\mathbb{A}, \mathbb{FI}_{Pre}) \tag{11}$$

$$Imp_{post} \leftarrow 1 - nH(\mathbb{A}, \mathbb{FI}_{Post}) \tag{12}$$

where, $\mathrm{nH}(\mathbb{A}, \mathbb{FI}_{\mathrm{Pre}})$ and $\mathrm{nH}(\mathbb{A}, \mathbb{FI}_{\mathrm{Post}})$ are normalized entropy of an area before and after the occurrence of floods. Thus, the entropy model of AA sub unit measures and reflects the contribution of influencing factors to flooding in the area. Higher weight variables contribute more to flood susceptibility than lower weight factors. Based on factors' weights, a final coastal FVI can be prepared. This helps in removing human bias in the decision-making. Integration of AA sub unit with SS sub unit in FVC provides robust weighting approach to assess the risks associated with flood areas.

3.3. Flood vulnerability binder at output phase

In the output phase, FVB scores are calculated for each area before and after floods respectively. $\mathrm{FVB_{Pre}}$ is calculated by taking the product of $\mathrm{Imp_{pre}}$ and $\mathrm{Scr_{pre}}$ using (13). Similarly, $\mathrm{FVB_{Post}}$ is calculated by multiplying $\mathrm{Imp_{post}}$ and $\mathrm{Scr_{post}}$ using (14). Finally, this phase computes k-FVI by taking the product of $\mathrm{FVB_{Pre}}$ and $\mathrm{FVB_{Post}}$ using (15). Lastly the affected areas are ranked by sorting the areas in ascending order of k-FVI. Higher the vulnerability, higher the rank. Advantage of FVB is that ranking is not done on basis of SS but on combination of SS with AA, so that unified importance of an area is also considered along with the transparent and robust score of the affected area.

$$FVB_{Pre} \leftarrow Imp_{pre} \times Scr_{pre} \tag{13}$$

$$FVB_{Post} \leftarrow Imp_{post} \times Scr_{post} \tag{14}$$

$$k\_FVI \leftarrow FVB_{Pre} \times FVB_{Post} \tag{15}$$

4. RESULTS AND DISCUSSION

The authors prove the efficacy of proposed k-FVI, a novel FVI by conducting experiments on flood data of Kerala districts [10]. Utilising data from 2018 Kerala floods, the flood susceptibility of the state's 14 districts is evaluated. The comparative analysis of k-FVI with existing FVIs proves its efficacy as a flood vulnerability score estimate. The results assess how vulnerable one district is to flood in comparison to another district.

4.1. Data description

As per the dataset, 14 districts were analyzed on 27 flood indicators. As per their definition, authors have grouped them into $\mathbb{FI}_{Pre}$ and $\mathbb{FI}_{Post}$ as shown in Tables 1 and 2. As a prerequisite to TOPSIS, each flood indicator is categorized as benefit or cost criteria, shown by symbols (+) and (-) sign respectively. All these indicators have been equally weighed. Also, the indicators belong to different categories viz. Economic (S5, S6, P3), environmental (S1, P1), social (S2, S3, P2) and infrastructure (S4) in Table 1. The post flood indicators can also be categorized into economic (R4, E3, E10, E12), environmental (E6, E7, E9, E11), social (R3, E4, E5, E8), and infrastructure (R1, R2, E1, E2) as shown in Table 2. This categorization is done by authors as per their subject knowledge.

Table 1. $\mathbb{FI}_{Pre}$: set of pre-flood indicators

District	Sensitivity indicators						Preparedness indicators		
	S1 (+)	S2 (+)	S3 (+)	S4 (-)	S5 (+)	S6 (+)	P1 (-)	P2 (-)	P3 (-)
D1	163	1087	1508	3	66	70	5	93.02	0.133333
D2	149	1113	1061	1	63	75	3	94.09	0.066667
D3	60	1039	895	0	58	122	4	97.21	0.266667
D4	0	1080	657	0	22	26	2	90.09	0.533333
D5	67	1108	1031	6	40	63	7	95.08	0.333333
D6	117	1132	452	11	103	96	2	96.55	0.133333
D7	77	1100	1504	0	96	133	8	95.72	0.866667
D8	131	1098	1157	0	119	78	6	93.57	0.333333
D9	154	1067	627	15	58	31	9	89.31	0.466667
D10	67	1098	1316	2	54	58	3	95.08	0.6
D11	23	1136	852	1	85	52	4	95.1	0.933333
D12	62	1027	1072	2	66	58	6	95.89	1
D13	78	1035	384	2	53	59	4	89.03	0.733333
D14	180	1006	255	20	58	33	5	91.99	0.2

- S1: percentage departure; S2: sex ratio; S3: population density; S4: dams reservoir; S5: rural unemployment rate; and S6: urban unemployment rate
- P1: no. of stations; P2: literacy rate; and P3: EW %
- D1: Thiruvananthapuram; D2: Kollam; D3: Kottayam; D4: Kasargod; D5: Thrissur; D6: Pathanamthitta; D7: Alappuzha; D8: Malappuram; D9: Palakkad; D10: Kozhikode; D11: Kannur; D12: Ernakulam; D13: Wayanad; and D14: Idukki

To compute the flood vulnerability index (c-FVI) from the dataset [10], average value of the rainfall measured by different rainfall stations located in the districts from 10 Aug 2018 to 24 Aug 2018 has been calculated. Authors intent to show the efficacy of proposed k-FVI by comparing with c-FVI. The snapshot of the dataset for two districts (Alappuzha and Wayanad) is shown in Table 3. The colors stated in the table show the warning levels issued by the government. Very heavy rainfall (115.6 mm to 204.4 mm) is indicated by red directs the places to take immediate action. Orange implying heavy rainfall (64.5 mm to 115.5 mm) alerts the areas. Yellow implies district with rainfall (15.6 mm to 64.4 mm), to be put on watch state and there is no warning issued for districts indicated by green having light rainfall (2.5 mm to 15.5 mm). The districts of Kerala state were ranked in ascending order of c-FVI, with higher rank assigned to a district indicating that it is more vulnerable to floods in comparison to districts with lower rank. The results are demonstrated in Figure 2. It clearly depicts that district D1 is least vulnerable to floods. Districts D6 and D14 being the most vulnerable to floods should take risk remediation steps as taken by district D1 to become less susceptible to floods in future.

Table 2. $\mathbb{FI}_{Post}$: set of post-flood indicators

	Rehabilitation indicators				Exposure indicators											
District	R1 (-)	R2 (-)	R3 (-)	R4 (+)	E1 (+)	E2 (+)	E3 (+)	E4 (+)	E5 (+)	E6 (+)	E7 (+)	E8 (+)	E9 (+)	E10 (+)	E11 (+)	E12 (+)
D1	0	0	94	100	11	0	1357	6	13	411	2	3	0	0	2940	10
D2	0	0	168	50	5	2	870	28	28	478	8	5	0	0	1338	97
D3	48	21	788	1000	14	29	7171	33	55	631	4	8	14	44154	656	2527
D4	0	0	2	0	1	0	199	4	4	222	3	1	0	0	74	0
D5	100	50	1513	5000	72	26	3569	15	157	712	15	26	5	89635	18241	443
D6	25	18	4352	2500	3	8	12085	46	39	1024	4	35	9	42406	32775	306
D7	350	802	2126	4000	43	0	12096	90	135	838	42	79	19	58611	18990	203
D8	0	0	213	100	30	30	5275	24	56	2002	27	19	2	0	3731	30
D9	0	0	165	200	20	20	6250	26	88	1859	22	28	2	0	3604	77
D10	0	0	399	150	16	9	627	7	31	654	7	12	15	0	1338	49
D11	0	0	37	2000	6	17	927	9	18	913	6	6	0	0	3216	36
D12	0	0	1582	6000	58	0	1297	56	178	1502	22	50	10	78209	1684	718
D13	0	0	451	1000	6	47	1877	35	78	910	6	39	9	3988	9350	0
D14	0	0	363	5000	54	143	5746	37	47	79.6	20	19	2	0	1445	109

- R1: repair of embankments; R2: repair of pumps; R3: no_of_camps; and R4: total cost of search and rescue
- E1: fatalities; E2: no_of landslides; E3: >33% crop loss extent (ha); E4: no. of school damaged; E5: no. of Anganwadi's damaged; E6: LSG roads (KM) damaged; E7: no. of primary health centers damaged; E8: no. of Panchayat owned buildings damaged; E9: damaged law and order stations; E10: Number of damaged drinking water structures; E11: severely damaged houses; and E12: loss in marine sector
- D1: Thiruvananthapuram; D2: Kollam; D3: Kottayam; D4: Kasargod; D5: Thrissur; D6: Pathanamthitta; D7: Alappuzha; D8: Malappuram; D9: Palakkad; D10: Kozhikode; D11: Kannur; D12: Ernakulam; D13: Wayanad; and D14: Idukki

Table 3. Dataset for two districts Alappuzha and Wayanad

District	Date	Actual rainfall	Predicted rainfall
Alappuzha	10-08-2018	Green	Yellow
Alappuzha	11-08-2018	Green	Red
Alappuzha	12-08-2018	Green	Red
Alappuzha	13-08-2018	Green	Orange
Alappuzha	14-08-2018	Green	Orange
Alappuzha	15-08-2018	Red	Orange
Alappuzha	16-08-2018	Red	Orange
Alappuzha	17-08-2018	Yellow	Orange
Alappuzha	18-08-2018	Green	Yellow
Alappuzha	19-08-2018	Green	Yellow
Alappuzha	20-08-2018	Green	Green
Alappuzha	21-08-2018	Green	Green
Alappuzha	22-08-2018	Green	Green
Alappuzha	23-08-2018	Yellow	Orange
Alappuzha	24-08-2018	Yellow	Yellow

District	Date	Actual rainfall	Predicted rainfall
Wayanad	10-08-2018	Yellow	Red
Wayanad	11-08-2018	Green	Red
Wayanad	12-08-2018	Green	Red
Wayanad	13-08-2018	Yellow	Red
Wayanad	14-08-2018	Orange	Red
Wayanad	15-08-2018	Red	Red
Wayanad	16-08-2018	Orange	Red
Wayanad	17-08-2018	Orange	Red
Wayanad	18-08-2018	Yellow	Yellow
Wayanad	19-08-2018	Green	Yellow
Wayanad	20-08-2018	Green	Green
Wayanad	21-08-2018	Green	Green
Wayanad	22-08-2018	Green	Green
Wayanad	23-08-2018	Red	Orange
Wayanad	24-08-2018	Red	Yellow

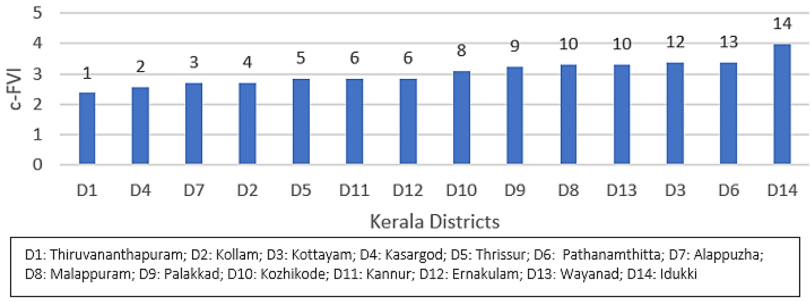


Figure 2. Ranks of districts generated by c-FVI method

4.2. Performance evaluation of existing FVI using three standard indicator categories

TOPSIS scores were obtained for three standard indicator categories viz. $\mathbb{E}$, $\mathbb{S}$, and $\mathbb{AC}$. Using (1), (2), (3), and (4), vulnerability index ($\mathbb{V}$) was computed by methods M1, M2, M3, and M4 respectively. The ranks obtained by these methods and c-FVI are shown in Table 4. To compare V obtained by these four methods with that of c-FVI, root mean square error (RMSE) was computed and is shown in last column of the table. It is clear from RMSE values that method M4 having least error is the best so far.

Table 4. Comparison of existing FVI methods (M1–M4)

District method	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D11	D12	D13	D14	RMSE
	District ranks														
c- FVI	1	4	12	2	5	13	3	10	9	8	6	6	10	14	Nil
M1	9	4	2	10	11	13	12	1	14	7	5	3	6	8	6.05
M2	11	4	2	10	9	12	1	3	14	7	8	5	6	13	5.22
M3	9	8	2	12	4	11	1	5	13	7	9	3	6	14	5.10
M4	10	4	2	9	5	12	1	3	13	6	11	8	7	14	4.94

D1: Thiruvananthapuram; D2: Kollam; D3: Kottayam; D4: Kasargod; D5: Thrissur; D6: Pathanamthitta; D7: Alappuzha; D8: Malappuram; D9: Palakkad; D10: Kozhikode; D11: Kannur; D12: Ernakulam; D13: Wayanad; and D14: Idukki

4.3. Performance evaluation of existing FVI using preparedness and rehabilitation indicators

The authors recommend to improve M4 further, with the aim to improve the computation of vulnerability index ($\mathbb{V}$). The improvement is based on using proposed division of $\mathbb{AC}$ indicator into $\mathbb{P}$ and $\mathbb{R}$ indicators; instead of using three standard indicator categories available in literature. Replacing $\mathbb{AC}$ by $\mathbb{P}$ and $\mathbb{R}$ in (1), (2), (3), and (4), authors get four modified methods viz. M5, M6, M7 and M8 which are represented by (16), (17), (18), and (19) respectively.

$$\mathbb{V} = \mathbb{E} * \mathbb{S} * \mathbb{P} * \mathbb{R} \tag{16}$$

$$\mathbb{V} = \mathbb{E} + \mathbb{S} - \mathbb{P} - \mathbb{R} \tag{17}$$

$$\mathbb{V} = (\mathbb{E} * \mathbb{S})/(\mathbb{P} + \mathbb{R}) \tag{18}$$

$$\mathbb{V} = (\mathbb{E} - (\mathbb{P} + \mathbb{R})) * \mathbb{S} \tag{19}$$

For all the fourteen districts TOPSIS scores was computed for $\mathbb{P}$, $\mathbb{R}$, $\mathbb{S}$, and $\mathbb{E}$. Then, modified vulnerability was obtained for these methods M5, M6, M7 and M8 using (16), (17), (18) and (19) respectively. The new ranks thus obtained by these methods and c-FVI are shown in Table 5. RMSE between the TOPSIS scores of districts based on each of these methods with respect to c-FVI was also calculated and is shown in last column of the Table. It is clear from RMSE values that, so far method M8 having least error is the best. It is also evident by comparing the last columns of Tables 4 and 5, RMSE is reduced considerably in M5 as compared to M1. Likewise, RMSE is reduced in M6, M7 and M8 in comparison to M2, M3 and M4 respectively. Thus, the authors conclude that the division of $\mathbb{AC}$ indicator into $\mathbb{P}$ and $\mathbb{R}$ indicators result into reduced RMSE, thereby formulating robust $\mathbb{V}$ scores.

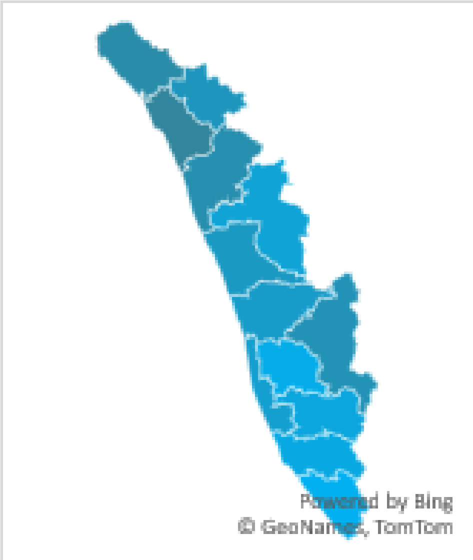
Table 5. Comparison of FVI methods (M5–M8)

District method	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D11	D12	D13	D14	RMSE
	District ranks														
c- FVI	1	4	12	2	5	13	3	10	9	8	6	6	10	14	Nil
M5	4	1	6	12	7	3	14	8	11	9	13	5	10	2	5.47
M6	10	11	5	12	9	13	1	6	8	4	7	2	3	14	4.94
M7	3	5	7	12	11	13	1	2	10	8	9	4	6	14	5.17
M8	10	11	5	12	8	13	1	9	7	4	6	2	3	14	4.92

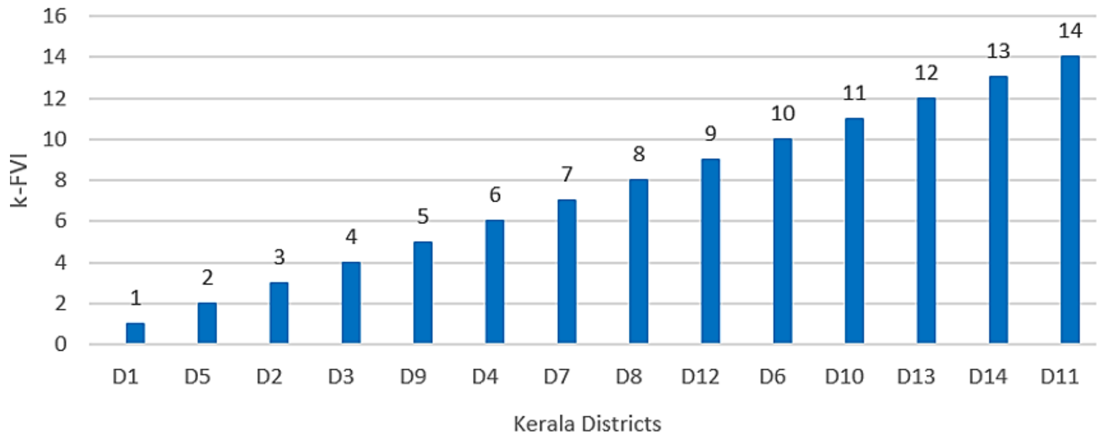
D1: Thiruvananthapuram; D2: Kollam; D3: Kottayam; D4: Kasargod; D5: Thrissur; D6: Pathanamthitta; D7: Alappuzha; D8: Malappuram; D9: Palakkad; D10: Kozhikode; D11: Kannur; D12: Ernakulam; D13: Wayanad; and D14: Idukki

4.4. Performance evaluation of proposed k-FVI

To improve the results further, FID clubbed $\mathbb{S}$ and $\mathbb{P}$ into pre-flood category and clubbed $\mathbb{E}$ and $\mathbb{R}$ into post-flood category. FVC calculated TOPSIS score in SS sub-unit and area importance in AA sub-unit. Finally, FVB calculated vulnerability scores by binding together scores obtained before and after the floods. Figure 3(a) shows the map of Kerala with the districts coloured according to the ranks obtained by k-FVI and the corresponding bar graph for the same is shown in Figure 3(b).



(a)



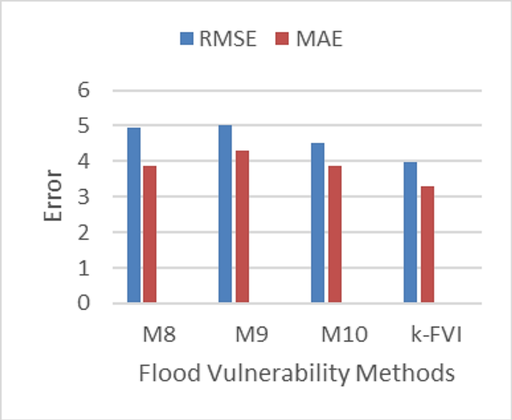
D1: Thiruvananthapuram; D2: Kollam; D3: Kottayam; D4: Kasargod; D5: Thrissur; D6: Pathanamthitta; D7: Alappuzha; D8: Malappuram; D9: Palakkad; D10: Kozhikode; D11: Kannur; D12: Ernakulam; D13: Wayanad; D14: Idukki

(b)

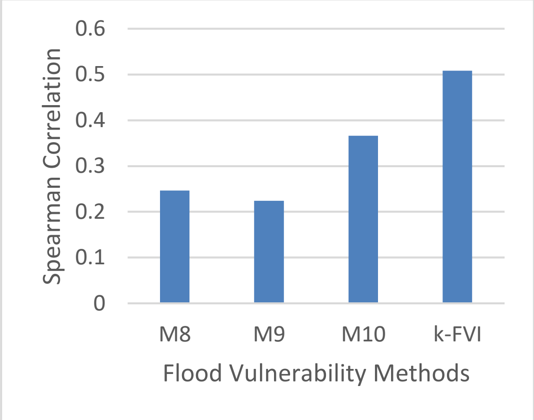
Figure 3. Ranks generated by k-FVI method; (a) map of Kerala and (b) bar graph

To prove the efficacy of process phase of the proposed k-FVI, the authors generated ranks by making following changes to the pseudocode shown in Figure 1. Case 1: authors omitted AA sub-unit of FVC and calculated ranks based on TOPSIS score generated by SS sub-unit of FVC unit. This method was named as M9. It did not consider the importance of an area in vulnerability calculations. Case 2: authors omitted post-flood scores calculated by SS sub-unit of FVC unit and ranks were generated by FVB using only pre-flood data. This method is named as M10. Finally, authors compared methods M8, M9, and M10 with the proposed method and found that RMSE and mean average error (MAE) both were least for proposed k-FVI when compared with c-FVI as shown in Figure 4(a). Since k-FVI is better than M9 so it is concluded that area analysis with entropy performed by AA sub-unit of FVC unit is of utmost importance. Since M10 has higher error values than k-FVI, it is concluded that post-flood indicators $\mathbb{E}$ and $\mathbb{R}$ play an integral role in lowering vulnerability index of an area in comparison to pre-flood indicators $\mathbb{S}$ and $\mathbb{P}$.

Further, authors obtained spearman rank correlation (ρ) of methods M8, M9, M10, and k-FVI with respect to c-FVI which is shown in Figure 4(b). It shows that spearman rank correlation (ρ) is highest for k-FVI suggesting that ranks given by c-FVI are best preserved by k-FVI. This concludes that division of $\mathbb{AC}$ indicator into $\mathbb{P}$ and $\mathbb{R}$ indicators before computing ranks proves to be beneficial.



(a)



(b)

Figure 4. Comparison of flood vulnerability methods and k-FVI with c-FVI; (a) error and (b) spearman correlation

4.5. Future scope

The methodology proposed in this study categorizes indicators into pre-flood and post-flood indicators based on subject knowledge of authors, and assigns equal weights to these indicators. The authors intend to perform a questionnaire analysis to find appropriate weights for the indicators and categorize them into pre-flood and post-flood indicators. Also, k-FVI may be measured for each component viz. environmental, infrastructure, economic and social to further strengthen the decision support system.

5. CONCLUSION

One of the most frequent and destructive natural catastrophes that affects people's lives on a socioeconomic level is flooding. Determining FVI of a given area is necessary in order to propose risk-reduction strategies. The k-FVI score proposed in this paper helps decision support system of the affected area to mitigate the adverse impact of floods. It detects area specific indicators viz. pre-flood Indicators and post-flood indicators and generates ranks for decision makers to reduce flood vulnerability in future. The advantage of the ranking given by k-FVI lies in the integration of entropy weights of an affected area with the TOPSIS score of the area. Comparative analysis of k-FVI with the existing FVIs, proves better efficacy of k-FVI.

REFERENCES

[1] Y. Hirabayashi *et al.*, "Global flood risk under climate change," *Nature Climate Change*, vol. 3, no. 9, pp. 816–821, Jun. 2013, doi: 10.1038/nclimate1911.

[2] N. N. Brooks and W. N. Adger, *Assessing and enhancing adaptive capacity*, Cambridge University Press, pp. 165-181, 2005.

[3] Jayaraj, "Post disaster reconstruction experiences in Andhra Pradesh in India," *International Conference on post-disaster reconstruction Meeting stakeholder interests*, 2006.

[4] F. J. Glago, "Flood disaster hazards; causes, impacts and management: a state-of-the-art review," in *Natural Hazards - Impacts, Adjustments and Resilience*, *IntechOpen*, 2021, doi: 10.5772/intechopen.95048.

[5] S. Divi, N. Dorasamy, and V. Nakum, "Disaster management in India: need for an integrated approach," *Disaster Advances*, pp. 60-68, 2022, doi: 10.25303/1508da060068.

[6] District Magistrate Agra, "District disaster management plan: Agra," pp. 1–175, 2011, [Online]. Available: http://agra.nic.in/pdf/DISASTER_PLAN_IN_ENGLISH.pdf

[7] E. Mortensen *et al*., "The potential of global coastal flood risk reduction using various DRR measures," *Natural Hazards and Earth System Sciences*, pp. 1381-1400, 2024, doi: 10.5194/nhess-24-1381-2024.

[8] N. Pramanick *et al*., "SAR based flood risk analysis: A case study Kerala flood 2018.," *Advances in space research*, pp. 1915-1929., 2022, doi: 10.1016/j.asr.2021.07.003.

[9] W. Yang, K. Xu, J. Lian, C. Ma, and L. Bin, "Integrated flood vulnerability assessment approach based on TOPSIS and Shannon entropy methods," *Ecological Indicators*, pp. 269-280, 2018, doi: 10.1016/j.ecolind.2018.02.01.

[10] A. Walia and N. Nusrat, "Kerala Floods 2018," National Institute of Disater Management, New Delhi, 2020.

[11] J. Rehman, O. Sohaib, M. Asif, and B. Pradhan, "Applying systems thinking to flood disaster management for a sustainable development," *International journal of disaster risk reduction*, 2019, 10.1016/j.ijdrr.2019.101101.

[12] S. Pathak, H. K. Panta, T. Bhandari, and K. P. Paudel, "Flood vulnerability and its influencing factors," *Natural Hazards*, vol. 104, pp. 2175-2196, 2020, doi: 10.1007/s11069-020-04267-3.

[13] C. Van, N. C. Tuan, T. Nguyen, D. Q. Tri, N. Anh, and D. D. Tran, "Flood vulnerability assessment and mapping: a case of Ben Hai-Thach Han River basin in Vietnam," *International Journal of Disaster Risk Reduction*, vol. 75, pp. 67-82, 2022, doi: 10.1016/j.ijdrr.2022.102969.
[14] J. Kind, W. J. Botzen, and J. Aerts, "Accounting for risk aversion, income distribution and social welfare in cost-benefit analysis for flood risk management," *WIREs Climate Change*, pp. 1-20, 2017, doi: 10.1002/wcc.446.
[15] H. Kreibich *et al.sss*, "The challenge of unprecedented floods and droughts in risk management," *Nature*, pp. 80-86, 2022, doi: 10.1038/s41586-022-04917-5.
[16] H. Ahuja, S. Narang, and R. Saxena, "A novel framework to strengthen early warning systems," *Engineering, Technology & Applied Science Research*, pp. 11917-11923, 2023.
[17] S. M. Weis *et al.*, "Assessing vulnerability: an integrated approach for mapping adaptive capacity, sensitivity and exposure," *Climatic Change*, pp.615-629, 2016, doi:10.1007/s10584-016-1642-0.
[18] H. Nasiri, M. Yusof, T. A. Ali, and M. K. Hussein, "District flood vulnerability index: urban decision-making tool," *International Journal of Environmental Science and Technology*, pp. 2249-2258, 2019, doi: 10.1007/s13762-018-1797-5.
[19] S. Rehman, M. Sahana, H. Hong, H. Sajjad, and B. B. Ahmed, "A systematic review on approaches and methods used for flood vulnerability assessment: framework for future research," *Natural Hazards*, vol. 96, pp. 975-998, 2019, doi: 10.1007/s11069-018-03567-z.
[20] N. Sahu and M. Mishra, "Assessing the vulnerability index of COVID-19 Pandemic in India.," *Geography, Environment, Sustainability*, pp. 131-139, 2021, doi: 10.24057/2071-9388-2021-059.
[21] A. I. Pathan, P. Agnihotri, S. Said, and D. Patel, "AHP and TOPSIS based flood risk assessment-a case study of the Navsari City, Gujarat, India," *Environmental Monitoring and Assessment*,, 2022, doi: 10.1007/s10661-022-10111-x.
[22] M. P. Mohanty, S. Mudgil, and S. Karmakar, "Flood management in India: a focussed review on the current status and future challenges," *International Journal of Disaster Risk Reduction*, vol. 49, p. 101660, 2020, doi: 10.1016/j.ijdrr.2020.101660.
[23] E. Rafiei-Sardooi, A. Azareh, B. Choubin, A. H. Mosavi, and J. J. Clague, "Evaluating urban flood risk using hybrid method of TOPSIS and machine learning," *International Journal of Disaster Risk Reduction*, pp. 102614, 2021, doi: 10.1016/j.ijdrr.2021.102614.
[24] R. Mitra, J. Das, and M. Kamruzzaman, "Application of TOPSIS method for flood susceptibility mapping using Excel and GIS," *MethodsX*, p. 102263, 2023, doi: 10.1016/j.mex.2023.102263.
[25] R. Mitra and J. Das, "A comparative assessment of flood susceptibility modelling of GIS-based TOPSIS, VIKOR, and EDAS techniques in the Sub-Himalayan foothills region of Eastern India," *Environmental Science and Pollution Research*, pp. 16036–16067, 2023, doi : 10.21203/rs.3.rs-1710264/v1.
[26] H. Ahuja, S. Narang, S. Kaur, and R. Saxena, "Entropy for item inclination in sub-community based recommender system," *International Journal of Advanced Technology and Engineering Exploration*, pp. 1111-1133, 2022, doi: 10.19101/IJATEE.2021.875768.
[27] C. E. Shannon, "Prediction and entropy of printed English," *Bell System Technical Journal*, vol. 30, no. 1, pp. 50-64, 1951, doi: 10.1002/j.1538-7305.1951.tb01366.x.
[28] A. Haghizadeh, S. Siahkamari, A. Haghiabi, and O. Rahmati, "Forecasting flood-prone areas using Shannon's entropy model," *Journal of Earth System Science*, 2017, doi: 10.1007/s12040-017-0819-x.
[29] R. Liu *et al.*, "Integrating entropy-based Naïve Bayes and GIS for spatial evaluation of flood hazard," *Risk Analysis*, pp. 756–773, 2017, doi: 10.1111/risa.12698.
[30] J. Lian, W. Yang, K. Xu, and C. Ma, "Flash flood vulnerability assessment for small catchments with a material flow approach.," *Nat. Hazards*, pp. 699–719, 2017, doi: 10.1007/s11069-017-2887-2.
[31] B. Liu, *Modelling multi-hazard risk assessment: a case study in the Yangtze River Delta, China.*, UK : University of Leeds, Leeds, 2015
[32] Q. Zhang, X. Gu, V. P. Singh, P. Shi, and P. Sun, "More frequent flooding? Changes in flood frequency in the Pearl River basin, China, since 1951 and over the past 1000 years," *Hydrology and Earth System Sciences*, pp. 2637–2653, 2018, doi: 10.5194/hess-22-2637-2018.
[33] G. Ziarh, M. Asaduzzaman, A. Dewan, M. Nashwan, and S. Shahid, "Integration of catastrophe and entropy theories for flood risk mapping in peninsular Malaysia," *Journal of Flood Risk Management*, 2020, doi: 10.1111/jfr3.12686.
[34] H. Al-Hinai and R. Abdalla, "Mapping coastal flood susceptible areas using shannon's entropy model: the case of Muscat Governorate, Oman," *ISPRS International Journal of Geo-Information*, vol. 10, no. 4, p. 252, Apr. 2021, doi: 10.3390/ijgi10040252.
[35] A. M. Al-Abadi, S. Shahid, and A. K. Al-Ali, "A GIS-based integration of catastrophe theory and analytical hierarchy process for mapping flood susceptibility: A case study of Teeb area, Southern Iraq," *Environmental Earth Sciences*, vol. 75, no. 687, 2016, doi: 10.1007/s12665-016-5523-7.
[36] A. Castillo, F. Castelli, and D. Entekhabi, "An entropy-based measure of hydrologic complexity and its applications," *Water Resources Research*, pp. 5145–5160, 2015, doi: 10.1002/2014WR016035.

BIOGRAPHIES OF AUTHORS

Geeta Aggarwal is an Associate Professor in Department of Computer Science, PGDAV College, University of Delhi. She graduated in Computer Science from Miranda House, University of Delhi in 1988 and she completed her Masters in Computer Science from Banasthali Vidyapeeth in 1990. She received Ph.D. in Computer Science from University of Delhi. She has more than 30 years of teaching experience. She has published research papers in various reputed international journals and conferences. She can be contacted at email: geeta.gupta@pgdav.du.ac.in.

Harita Ahuja received her Master's degree in Computer Applications in 2004 from GGSIP University, New Delhi and completed her Doctoral studies from Department of Computer Science, University of Delhi in 2014. She is currently working as Associate Professor in Department of Computer Science, Acharya Narendra Dev College, University of Delhi and has 17 years of teaching experience. Her research interest spans the area of hybrid recommender systems, disaster management and information theory. She can be contacted at email: haritaahuja@andc.du.ac.in.

Sunita Narang is working as an Associate Professor in the Department of Computer Science, Acharya Narendra Dev College, University of Delhi. She completed Masters of Computer Applications from Jawaharlal Nehru University in 1997. She received Ph.D. in the area of Financial Derivatives from Faculty of Management Studies, University of Delhi in 2013. She has published research papers in various reputed journals and conferences. She was involved in a few inter-disciplinary DU Innovation projects where she guided students. She was awarded Teaching Excellence award for Innovation for one of the DU Innovation projects in May 2015. She can be contacted at email: sunitanarang@andc.du.ac.in.

Seema Aggarwal graduated from St. Stephens College, University of Delhi in 1989 and completed her Master's in computer applications (MCA) from University of Delhi in 1992. Post her MCA, she worked in the IT industry developing system software including Intelligent SCSI device drivers and fault tolerant systems. She did her Ph.D. from University of Delhi in 2013. She is currently working as Associate Professor in Department of Computer Science, Miranda House, University of Delhi and has more than 25 years of teaching experience. Her areas of interests include fault tolerant systems, decision support systems and data analytics. She can be contacted at email: seema.aggarwal@mirandahouse.ac.in.