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An Assessment of Flash Flood Vulnerable Zones Using Integrated Grey Fuzzy Analytic Hierarchy Process-based Model for a Himalayan Watershed

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Abstract

Flash flood is the most recurrent natural threat in the northeastern part of India, especially during the peak of the monsoon season. Considering the exponential rise in the frequency of flash flood events, identifying the Flash Flood Vulnerable Zones (FFVZs) is one of the most crucial findings to limit their negative consequences. In this study, Grey Fuzzy Analytic Hierarchy Process (GFAHP) based model integrated with the Geographic Information System (GIS) is implemented to assess the flash flood vulnerability in the Ranikhola watershed, East Sikkim, India. The GFAHP combines the benefits of all the traditional Multi-Criteria Decision-Making (MCDM) approaches. The Fuzzy Analytic Hierarchy Process (FAHP) is used to compute the weights, while the weight coefficients are evaluated using the Grey method. A novel Flash Flood Vulnerability Index (FFVI) is proposed to assess the flash flood vulnerability that takes into account twelve natural and anthropogenic parameters. Further, the FFVI map is classified into three FFVZs: low, moderate, and high. The efficacy of the flash flood vulnerability map is calculated by a single effectiveness value (EV), and the result is between moderate and more significant. The sensitivity analysis results show the influence of individual attributes on FFVI and FFVZs.

Keywords: Flash Flood Vulnerability Index (FFVI), Flash Flood Vulnerability Zones (FFVZs), Grey Fuzzy Analytic Hierarchy Process (GFAHP), Geographic Information Systems (GIS).

1. Introduction

Flash flood is one of the most severe natural hazards that occurs within a small watershed, caused by a significant amount of rainfall over a short period of time (Carmen Llasat et al. 2017). In the Himalayan watersheds, with their extreme topography and enormous foothill zone, a heavy monsoon rainfall brings flash floods to the upstream
highlands and the downstream plains, causing enormous human suffering and loss of life, crop damage, and increased economic losses. Massive flash floods and disasters, such as landslides, are caused by a shorter period of high-intensity and more extended periods of prolonged rainfall, particularly in a high mountainous watershed (Twaróg 2017). Therefore, identifying Flash Flood Vulnerable Zones (FFVZs) is crucial for flood risk mitigation and management and developing mitigation strategies for flash flood susceptibility areas. During the 20th century, flood hazard prediction was performed by applying hydrologic coupled hydraulic models (Refsgaard et al. 1988; Ramírez 2000). However, these models necessitate a considerable amount of hydroclimatic and hydraulic data, which is scarce in most of the Himalayan mountainous watersheds.

In recent decades integrated application of Remote Sensing (RS) and Geographic Information Systems (GIS) tools have attracted much attention in flood vulnerability studies for their effectiveness, as well as rapid and easy access to data (Islam et al. 2022). For the past two decades, many methodologies have been used to identify and quantify FFVZs across several watersheds, including frequency ratio (Rahmati et al. 2016; Shafapour Tehrany et al. 2019), artificial neural networks (Falah et al. 2019), support vector machines (Tehrany et al. 2014; Choubin et al. 2019), decision trees (Costache 2019), etc. However, the Analytic Hierarchy Process (AHP) is the most extensively used Multi-Criteria Decision-Making (MCDM) method (Saaty 1990; Das and Gupta 2021). The Fuzzy AHP (FAHP) approach is a progressive explanatory method that evolved from the conventional AHP (Chang, 1996; Costache et al., 2022; Meshram et al., 2019). The FAHP model has been used for analyzing complicated decision-making problems (i.e., flood risk mapping) with incomparable experts’ priority criteria integrated with GIS (Hategekimana et al. 2018; Abu El-Magd et al. 2020; Hadian et al. 2022). Since, an adequate assessment of FAHP is not available, an integrated Grey Fuzzy Analytic Hierarchy Process (GFAHP) is proposed to examine FFVZs in the current study. Also, an index-based overlay approach is carried out to predict flash flood vulnerability by developing the Flash Flood Vulnerability Index (FFVI). In this present study, FFVZs are delineated based on indirect implication analysis of affecting parameters or attributes such as 1) Terrain Ruggedness Index (TRI), 2) Topographic Wetness Index (TWI), 3) Plan Curvature, 4) Drainage Density (DD), 5) Dissection Index (DI), 6) Slope, 7) Topographic Position Index-based Landform (TPI-Landform), 8) Soil Type, 9) Geological Formation, 10) Elevation, 11) Land Use Land Cover (LULC), and 12) Annual
Average Frequency of Heavy Rainfall Days (AAFHRD). A sensitivity analysis is carried out to determine the impact of individual attributes on the computation of FFVI and the areal distribution of final FFVZs.

Fig. 1. Location of the Ranikhola Watershed, East Sikkim, India.
2. Study Area

The Ranikhola Watershed is located in East District, Sikkim, India. The total watersheds’ area of 254 km$^2$ is bounded by 27°14′15″ N - 28°23′49″ N latitudes and 88°29′25″ E - 88°43′19″ E longitudes along the NE-SW direction. It has an elevation ranging from 4061 m to 292 m. This leaf-shaped watershed has experienced an average annual rainfall of 3085 mm and an average monsoon rainfall of 2214 mm. The maximum monthly average rainfall occurs in July (685.6 mm), followed by June (596.6 mm) and August (543.2 mm). The average maximum temperature is 17°C observed in the summer season (April to June), while the average minimum temperature is less than 0°C, observed in the peak of the winter season (December to January). The drainage pattern is mostly dendritic. A single operational rain gauge station near Gangtok, the capital of Sikkim, is located between the Ranikhola and Rora Chu Rivers. And a single active gauging station is situated near Singtam, where the Ranikhola River meets the Teesta River on its left bank. The heavy monsoon rainfall is one of the significant factors causing frequent landslides every year. A total of 55 major Landslide Inventory Points (LIPs) with in the Ranikhola watershed are depicted in Fig. 1. These LIPs were acquired from the Bhukosh site (https://bhukosh.gsi.gov.in) of the Geological Survey of India (GSI). During the monsoon season, landslides are significant contributors to flash floods in their upstream areas. According to the National Flood Vulnerability Assessment System (https://bhuvan-app1.nrsc.gov.in), the entire watershed is characterized as high flood vulnerable (10%) and very high flood vulnerable (90%).

3. Materials and Methods

3.1. Datasets

A high-resolution (12.5 m) terrain corrected Advanced Land Observing Satellite Phased Array type L-band Synthetic Aperture Radar (ALOS PALSAR) Digital Elevation Model (DEM) was collected from the Alaska Satellite Facility (ASF) Distributed Active Archive Center (DAAC). The study area’s high-resolution (5.8 m) satellite data, Linear Imaging Self-Scanner-IV (LISS-IV), was acquired from the National Remote Sensing Centre (NRSC), Hyderabad, Telangana, India, for 2020. Three toposheets were collected from the Open Data Archive of Survey of India (SoI) on a 1:50,000 scale. Survey of India Toposheet No. – 78 A/12 (1932) on a 1:63,360 scale was collected from the historical maps of South Asia, due to the unavailability of this toposheet in the Survey of India Open Data Archive. The geology map and the soil properties map for the Ranikhola watershed were prepared from the Geology and Soil Map of Sikkim on a 1.100000 scale (CISMHE 2007; Sivakumar and Ghosh 2017). Gridded rainfall data (0.25°*0.25°, daily) for the
period from 1990 to 2020 was acquired from the India Meteorological Department (IMD). The annual average frequency of heavy rainfall days (AAFHRD, > 650 mm) map was collected from Climatic Research and Services, IMD report for Sikkim (Guhathakurta et al. 2020).

3.2. Methodology

3.2.1. Flash Flood Influencing Attributes

ALOS-PALSAR-DEM was used to estimate the primary topographic features. The TRI measures topographic heterogeneity quantitatively. Therefore, TRI is one of the influencing attributes that affect flash floods in topographically harsh watershed (Tehrany et al. 2019; Das and Gupta 2021; Arabameri et al. 2022). TRI was calculated using the difference in absolute elevation between a set of eight neighborhoods surrounding a central pixel, as

\[
TRI = \sqrt{\sum (X_{ij} - X_{i0})^2}
\]

Where \(X_{ij}\) represents the relative elevation value of each neighbor cell to the central cell \(X_{i0}\) (Riley et al. 1999), equation (1) is further modified to normalize the raster values by applying Principal Component Analysis (PCA) to reduce numerical complexity, boost performance, and increase index value stability (Habib 2021). The modified expression for estimating TRI is

\[
TRI = \frac{X_M - X_{\text{min}}}{X_{\text{max}} - X_{\text{min}}}
\]

Where \(X_m\) represents the raster value of DEM, \(X_{\text{min}}\) is the minimum raster value, which is calculated by statistics of minimum values within eight neighborhoods for each input cell, \(X_{\text{max}}\) is the maximum raster value, which is calculated by statistics of maximum values within eight neighborhoods for each input cell.

TWI is used to detect hydrological flow routes. The variation in TWI values demonstrates how topography affects various hydrological processes. Flooded locations typically depict higher TWI values (Rahmati et al. 2016; Tehrany et al. 2019; Vignesh et al. 2021). The TWI can be computed as

\[
TWI = \ln \left( \frac{a}{\tan b} \right)
\]
where, \( a \) is the relative upslope catchment area per unit flow accumulation, and \( \tan b \) is the local slope (i.e., gradient) at a specific point.

This study area identified three types of plan curvature (i.e., convex, concave, and linear or flat). The slopes were measured in percent and degree, and they were divided into seven categories, ranging from flat to very steep. The contours were digitized at 20 m and 100 m intervals from a DEM (for viewing and presentation). As a function of elevation, contours were allocated identity numbers (i.e., ID). By linking triplets of nodes and constructing non-overlapped triangles, a Triangular Irregular Network (TIN) based relief map is created (Li et al. 2004). TIN is well suited to simulating complicated natural topography, such as the Ranikhola watershed, and provides better elevation range information. These three factors have a significant impact on flash-flood generation in an effective rainfall incident (Doorga et al. 2022; Hadian et al. 2022).

Water laden with soil is washed downstream via soil erosion, resulting in thick sediment layers that obstruct the flow of streams, perhaps resulting in flooding. In this present study, DI is used as an indicator of soil erosion intensity (Deolia and Pande 2014; Mahabaleshwara and Nagabhushan 2014) which can be another influencing attribute of the flash flood. The ratio of maximal relative relief to the highest absolute relief was used to determine the DI (Senthilvelan 2017). It is an essential morphometric indicator of the characteristics and extent of terrain dissection. The DI value ranges from zero (no dissection) to one (complete dissection or vertical cliff).

Drainage network extraction is based on deriving surface drainage features, which is a fundamental requirement in all hydrological studies (Mangan et al. 2019). The general procedure for extracting drainage networks from DEM is as follows: (1) filling the depressions in DEM, (2) determining the flow direction, (3) calculating the flow accumulation values, (4) calibrating the flow accumulation threshold (FAT) values, and (5) deriving the drainage network(s) according to FAT values (Chang 2019). The mean value of the flow accumulation raster computed as 1394 is used as the FAT (Gou-an 2000). The drainage network was extracted using Strahler’s formula (Strahler 1964). This drainage network was used to estimate the drainage density (DD). DD indicated the closeness of channel spacing and was calculated by the ratio of the total length of all order streams to the basin area (Horton 1945). The DD is also one of the leading conditioning elements that strongly influences the incidence of flood occurrence (Rahmati et al. 2016; Arabameri et al. 2022; Nsangou et al. 2022; Vilasan and Kapse 2022).
The Topographic position index (TPI) is a differentiated Z-value (i.e., elevation) of each cell from the mean elevation value of a specified neighborhood cell of DEM. Positive values of TPI signify grids located at a higher level than their surroundings, like ridges, negative values of TPI signify grids situated at a lower level than their surroundings, like valleys, and zero values indicate plains. This study executed the landform classification by standardizing the TPI grids and combining the 25 m and 200 m TPI grids. ‘TPI 25’ is used as a small neighborhood, and ‘TPI 200’ is used as a large neighborhood as the identification of landforms (i.e., geomorphology) is challenging, using a single TPI scale factor. Variation of landforms is also considered an influential factor for flash flooding (Das and Gupta 2021; Vignesh et al. 2021; Costache et al. 2022).

The geological formation and soil properties are one of the prime factors for the occurrence of flash floods (Falah et al. 2019; Tehrany et al. 2019; Hadian et al. 2022). Rainfall distribution over the surface of the watershed also has a significant impact on the generating flash flood in hilly terrain (Islam et al. 2022). Due to the small size of this watershed, having a single rain gauge station, the spatially varied AAFHRD is considered another prime influencing attribute. Land Use Land Cover (LULC) classification was performed for the acquired LISS-IV datasets by generating standard False Color Composite (FCC) images. Supervised Classification technique with Maximum Likelihood Classifier (MLC) algorithm is applied to the FCC images after geo-rectifying each data tile for 2020. Here LULC is also one of the significant factors affecting flash floods (Abu El-Magd et al. 2020; Vignesh et al. 2021; Doorga et al. 2022; Vilasan and Kapse 2022).

### 3.2.2. Flash Flood Vulnerability Index (FFVI)

The conventional index approach is employed to produce the Flash Flood Vulnerability Index (FFVI). All influencing vector layers (e.g., AAFHRD, soil type, geological formation) are transformed into raster layer of spatial resolution of 12.5 m. And other raster layers (e.g., LULC), having a higher spatial resolution (5.8 m), are upscaled into the exact spatial resolution (12.5 m) as DEM. Individual attributes or parameters are categorized into sub-attributes, and weights are applied accordingly in the initial phase. All classified maps are integrated using a weighted overlay method to develop a vulnerability index map and reclassified into three different FFVZs. The FFVI can be estimated as

$$\text{FFVI}_{px,py} = \sum_{i=1}^{N_k} W_i \left( \sum_{k=1}^{N_{SA}} w^k_i X^k_i \left( C^k_{px,py} \right)_i \right)$$

(4)
where, \(i\) and \(k\) are attribute and sub-attributes, respectively; the number of attributes considered is indicated by \(N_A\); for the \(i\)th attribute, \(N_{SA}\) denotes the total number of sub-attributes; \(W_i\) and \(w_{ik}\) are the normalized weight of the \(i\)th attributes and the normalized weight of the \(k\)th sub-attributes for the \(i\)th attribute, respectively; \((C_{px,py})_i\) represent the pixel's class value \((px, py)\) for the \(i\)th attribute; the sub-attribute interval is denoted by \(A'_{ik}\).

An indicator function for the \(k\)th sub-attribute of the \(i\)th attribute is signified by \(\chi_{A'_{ik}}\). It is expressed as

\[
\chi_{A'_{ik}}\left(C_{px,py}^i\right) = \begin{cases} 
0, & \text{if } \left(C_{px,py}^i\right)_i \notin A'_{ik} \\
1, & \text{if } \left(C_{px,py}^i\right)_i \in A'_{ik}
\end{cases}
\]  

(5)

3.2.3. Grey Fuzzy Analytic Hierarchy Process (GFAHP) Assessment Model

3.2.3.1. Fuzzy Analytic Hierarchy Process (FAHP) methodology

The AHP was developed by Saaty (1980), which is one of the most knowledge-based, effective, and systematized mathematical methods for addressing complicated decision problems. However, the FAHP method with a triangular fuzzification approach that portrays ambiguity in human judgments can produce more accurate, detailed, and realistic results (Chang, 1996; Vilasan & Kapse, 2022). The judgment matrices are generated by ranking the attributes and their sub-attributes between 1 to 9 (e.g., extremely significant is represented by nine and extreme insignificant is represented by one) according to their importance (Sahoo et al. 2016). These matrices are developed by pairwise comparison to determine component priorities based on their relative importance in attaining the actual goal (Abijith et al. 2020; Vignesh et al. 2021). Then the fuzzy triangular scale (i.e., Triplets) is applied to the individual entries of the matrices (Liou and Wang 1992; Chowdhury and Quaddus 2016; Mohamad and Zainuddin 2021) (Table 1).

**Table 1.** AHP and FAHP scales were used in this study.

<table>
<thead>
<tr>
<th>Categories</th>
<th>Rank of AHP</th>
<th>Scales of Fuzzy AHP</th>
<th>Scales of Fuzzy AHP</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Triplets</td>
<td>Reciprocal of Triplets</td>
</tr>
<tr>
<td>Extremely Significant</td>
<td>9</td>
<td>(8, 9, 10)</td>
<td>(0.10, 0.11, 0.13)</td>
</tr>
<tr>
<td>Strongly Significant</td>
<td>8</td>
<td>(7, 8, 9)</td>
<td>(0.11, 0.13, 0.14)</td>
</tr>
<tr>
<td>More Significant</td>
<td>7</td>
<td>(6, 7, 8)</td>
<td>(0.13, 0.14, 0.17)</td>
</tr>
<tr>
<td>Moderately Significant</td>
<td>6</td>
<td>(5, 6, 7)</td>
<td>(0.14, 0.17, 0.20)</td>
</tr>
<tr>
<td>Equally Significant</td>
<td>5</td>
<td>(4, 5, 6)</td>
<td>(0.17, 0.20, 0.25)</td>
</tr>
<tr>
<td>Intermediate</td>
<td>4.5</td>
<td>(3.50, 4.50, 5.50)</td>
<td>(0.18, 0.22, 0.29)</td>
</tr>
</tbody>
</table>
A triplet, $\tilde{A}_i$ on Rank of AHP ($R$) can be depicted as $(l, m, n)$, and its membership function can be expressed as (Lee 2015)

$$
\mu_{A_i(s)} =
\begin{cases}
0, x \leq l \\
\frac{x-l}{m-l}, l \leq x \leq m \\
\frac{x-u}{m-u}, m \leq x \leq u \\
0, otherwise
\end{cases}
$$

(6)

The arithmetic operations of two triplets, $\tilde{A}_1 = (q, r, s)$ and $\tilde{A}_2 = (t, u, v)$, can be executed as

$$
\tilde{A}_1 \oplus \tilde{A}_2 = (q + t, r + u, s + v)
$$

(7)

$$
\tilde{A}_1 \otimes \tilde{A}_2 = (q \times t, r \times u, s \times v)
$$

(8)

$$
\tilde{A}_i^{-1} = \left(\frac{1}{s}, \frac{1}{r}, \frac{1}{q}\right)
$$

(9)

$$
\lambda \otimes \tilde{A}_i = (\lambda \times q, \lambda \times r, \lambda \times s) (\lambda > 0, \lambda \in R)
$$

(10)

The relative fuzzy weights are computed as

$$
F_{W_1} = \frac{GM_1}{\sum_{i=1}^{N}GM_i}, F_{W_2} = \frac{GM_2}{\sum_{i=1}^{N}GM_i}, F_{W_n} = \frac{GM_n}{\sum_{i=1}^{N}GM_n}
$$

(11)

The geometric mean(s) ($GM_i$) of the $i^{th}$ row(s) of the judgment matrix can be estimated as $GM_i = \sqrt[N]{a_{i1}a_{i2}...a_{iN}}$. 

The relative weight \((W_i)\) is computed by applying the defuzzification weighted average approach as

\[
W_i = \frac{F_{W_i} \oplus F_{W_m} \oplus F_{W_r}}{3}
\]  

(12)

The Consistency Ratio (CR) computation is used for evaluating the judgment matrices by their acceptable value, i.e., \(CR < 0.1\). However, a reconstruction of the judgment matrix is needed for \(CR \geq 0.1\). Computation of CR involves the following steps.

\[
CR = \frac{CI}{RCI}
\]  

(13)

Random Consistency Index (RCI) values are taken for each matrix from the standard table according to their \(N_A\) or \(N_{AF}\) (Alonso and Lamata 2006). The Consistency Index (CI) is calculated as

\[
CI = \frac{\lambda_{max} - N_A}{N_A - 1}
\]  

(14)

The maximum value of eigenvalue or latent root \(\lambda_{max}\) is evaluated as

\[
\lambda_{max} = \sum_{m=1}^{N_A} \frac{(AW)_m}{N_AW_m}
\]  

(15)

where, \(W\) denotes the weight, which is represented by a column vector. The same sequential functioning approach must be followed for the estimation of \(w_k\). Finally, the FFVZ map is obtained by Eq. (4).

### 3.2.3.2 Grey-Analytic Hierarchy Process (G-AHP) Model

Grey Analytic Hierarchy Process (G-AHP) model is applied for structuring the remark set of the assessment index, \(v = (97531)^T\). The values are assigned based on an earlier scale (i.e., 9 to 1) against five ranks: excellent (9), good (7), moderate (5), bad (3), and worse (1). The grades: 8, 6, 4, and 2 are used to differentiate intermediate ranks from one another (Jin et al. 2007; Liu and Forrest 2010). The following steps are involved in determining total effectiveness assessment values:

Step 1. Construction of assessment sample matrix \((D)\):
where, \( d_{ij}^l \) is the \( j \)th assessment index value corresponding to sub-attribute \( B_k \), and \( l \) is the number of experts. The total number of sub-features is represented as \( N_{SA} = \sum_{i=1}^{N} N_{SA}^i \).

Step 2. Assessment of grey cluster determination:

Grey cluster ‘excellent’ \((e =1)\) with grey number \( \phi_1 \in [0, 9, \infty) \), of its whitenization function \( \zeta_{\phi_1}(x) \), can be expressed as

\[
\zeta_{\phi_1}(x) = \begin{cases} 
\frac{x}{9}, & 0 < x < 9 \\
1, & x \geq 9 \\
0, & \text{else}
\end{cases}
\]

Grey cluster ‘good’ \((e =2)\) with grey number \( \phi_2 \in [0,7,14) \), of its whitenization function \( \zeta_{\phi_2}(x) \), can be expressed as

\[
\zeta_{\phi_2}(x) = \begin{cases} 
1, & 0 < x \leq 7 \\
\frac{14-x}{7}, & 7 < x \leq 14 \\
0, & \text{else}
\end{cases}
\]

Grey cluster ‘moderate’ \((e =3)\) with grey number \( \phi_3 \in [0, 5, 10) \), of its whitenization function \( \zeta_{\phi_3}(x) \), can be expressed as

\[
\zeta_{\phi_3}(x) = \begin{cases} 
1, & 0 < x \leq 5 \\
\frac{10-x}{5}, & 5 < x \leq 10 \\
0, & \text{else}
\end{cases}
\]

Grey cluster ‘bad’ \((e =4)\) with grey number \( \phi_4 \in [0, 3, 6) \), of its whitenization function \( \zeta_{\phi_4}(x) \), can be expressed as

\[
\zeta_{\phi_4}(x) = \begin{cases} 
1, & 0 < x \leq 3 \\
\frac{6-x}{3}, & 3 < x \leq 6 \\
0, & \text{else}
\end{cases}
\]
Grey cluster ‘worse’ (e =5) with grey number $\phi_s \in \{0, 1, 2\}$, of its whitenization function $\xi_{\phi_5}(x)$, can be expressed as

$$
\xi_{\phi_5}(x) = \begin{cases} 
1, & 0 < x \leq 1 \\
1 - x, & 1 < x \leq 2 \\
0, & \text{else}
\end{cases}
$$

(21)

Step 3. Computation of grey assessment weight:

The evaluation coefficient for grey clusters can be represented as

$$
\delta_{pe} = \sum_{i=1}^{l} \xi_{\phi_i} \left(d_i^e\right)
$$

(22)

The total amount of grey assessment (with sub-attribute $B_k$) for individuals fitting all assessed grey clusters can be computed as

$$
\delta_p = \sum_{e=1}^{5} \delta_{pe}
$$

(23)

Therefore, the grey assessment weight of $e^{th}$ grey cluster can be expressed as

$$
r_e = \frac{\delta_{pe}}{\delta_p}
$$

(24)

Hence, the grey assessment weight vector for $k^{th}$ sub-attribute of an $i^{th}$ attribute is denoted as $r_k = (r_{k1}^1, r_{k1}^2, \ldots, r_{k1}^5, r_{k2}^1, r_{k2}^2, \ldots, r_{k2}^5, \ldots, r_{kN_{ik}}^1, r_{kN_{ik}}^2, \ldots, r_{kN_{ik}}^5)^T$. The grey assessment weight matrix for all assessed grey clusters can be expressed as

$$
R_i = \begin{bmatrix}
    r_{i1}^T \\
    r_{i2}^T \\
    \vdots \\
    r_{iN_{ik}}^T
\end{bmatrix}
\begin{bmatrix}
    r_{i1}^1 & r_{i1}^2 & \cdots & r_{i1}^5 \\
    r_{i2}^1 & r_{i2}^2 & \cdots & r_{i2}^5 \\
    \vdots & \vdots & \ddots & \vdots \\
    r_{iN_{ik}}^1 & r_{iN_{ik}}^2 & \cdots & r_{iN_{ik}}^5
\end{bmatrix}
$$

(25)

Step 4. Computation of total assessment value:

First, assessing $A_i$ synthetically, and then the conclusion of complete evaluation ($P_i$) can be determined as

$$
P_i = W_i^T R_i = (p_{i1}, p_{i2}, p_{i3}, p_{i4}, p_{i5})
$$

(26)

Therefore, the integrated conclusion of the complete evaluation can be determined as
When too much information is lost, judgment can be affected. Therefore, a single effectiveness value \((EV)\) is evaluated as

\[
EV = P_iV
\]

A judgment on the efficiency of FFVZs mapping can be reached based on the \(EV\) value.

### 3.2.4. Sensitivity Analysis

Sensitivity analysis is performed to analyze the robustness of the output in the occurrence of uncertainty, understanding the relationships between input attributes and the final result. In this study, the impact of all attributes on FFVI computation and FFVZs areal distribution is assessed by the sensitivity analysis. The following expression was employed to find the sensitivity of individual attributes.

\[
S_{FFVZ_j} = \left( \frac{S_j - S_{All}}{S_{All}} \right) \times 100
\]

where \(S\) represents the relative change of the areal distribution of FFVZs for the individual attributes. \(S_{All}\) is the areal distribution of individual FFVZs. \(S_j\) represents the areal distribution of FFVZs for \(j^{th}\) attribute. The weights of other attributes can be calculated by excluding the \(j^{th}\) attribute using Eqs (6) to (15). Finally, FFVZ\(_j\) delineating by calculating FFVI (Eq. 4) for \(j^{th}\) attribute.

### 4. Results and Analysis

Flash Flood Vulnerability Index (FFVI) is determined by the following attributes: Terrain Ruggedness Index (TRI), Topographic Wetness Index (TWI), Plan Curvature, Drainage Density (DD), Dissection Index (DI), Slope, Topographic Position Index-based Landform (TPI-Landform), Soil Type, Geological Formation, Elevation, Land Use Land Cover (LULC), and Annually Average Frequency of Heavy Rainfall days (AAFHRD).

1. **Terrain Ruggedness Index (TRI):** TRI is classified into five classes for the study area: (1) Very low (5.65%), (2) Low (20.96%), (3) Moderate (34.36%), (4) High (28.86%), and (5) Very High (10.17%), shown in Fig. 3 (c).
2. **Topographic Wetness Index (TWI):** TWI is categorized into five different categories: (1) Very low (22.92%), (2) Low (38.20%), (3) Moderate (25.20%), (4) High (10.56%), and (5) Very High (3.11%). A spatially averaged TWI value, known as mean TWI, was calculated, and the value is 5.40 in this study area (Fig. 3 (d)).

3. **Plan Curvature:** The plan curvature map (Fig. 2. (a)) depicts the concavity or convexity of the topography, which is significant for estimating FFVI. The regional distribution of the three texture classes of curvature shows only 32 km² area is linear or flat textured, 110.86 km² area is concave and 111.26 km² area is convex.

4. **Drainage Density (DD):** The drainage density is divided into five categories: (1) Very low (54.84%), (2) Low (21.48%), (3) Moderate (15.94%), (4) High (6.29%), and (5) Very High (1.45%). A low elevation section of this mountain watershed having permeable lithology of the surface has a high DD (Fig. 2. (c)).

5. **Dissection Index (DI):** DI was estimated by constructing 1km×1km DEM grids and five classes are distinguished with their ranges, very low (< 0.16), low (0.16 to 0.24), moderate (0.24 to 0.32), high (0.32 to 0.48), and extremely
high (> 0.48), as shown in Fig. 2. (b). Around 64% of the total area is moderately dissected. Lower reaches with a low or moderate slope have a higher DI than the upper reaches.

6. **Slope**: A slope is a unit of measurement for the change in elevation over distance, as shown in Fig. 2. (d) The slope can be measured in degrees or in percentages. Slopes are divided into seven categories, ranging from flat to highly steep. The ranges of slope classes are flat (0 -5%, 0 to 3°), gentle (5 to 9%, 3 to 5°), moderate (9 to 15%, 5 to 8.5°), strong (15 to 45%, 8.5 to 24°), extreme (45 to 70%, 24 to 35°), steep (70 to 100%, 35 to 45°), very steep (> 100%, >45°). The regional distribution shows around 38% area under strong slopy area, followed by 35% area under extreme, and 18% area under steep slopy area.

7. **Topographic Position Index-based Landform (TPI-Landform)**: A total of ten landform classes were assigned in the watershed. This classification is based on the standardized value of TPI grids of 25m and 200m. The final landform classification map for the Ranikhola watershed is shown in Fig. 3(a).

8. **Soil Type**: In the Ranikhola watershed, seven different types of soils were found, viz., (1) Coarse loamy cemented soil, loamy skeletal intrusive rocky surface (0.39%), (2) Coarse loamy excessive drainage rocky valley fill soil (19.29%), (3) Coarse loamy excessive drainage stony soil, fine and mixed loamy soil (40.16%), (4) Coarse loamy excessive drainage, weak structured soil (1.57%), (5) Fine loamy mixed soil, coarse loamy ever fragmental soil (26.77%), (6) Fine loamy weak, and mixed soil (4.72%), and (7) Loamy skeletal weathered soil, coarse loamy, rocky surface (7.09%). The primary soil type for our study area is Loamy soil (Fig. 4(a)).

9. **Geological Formation**: In our study region, we found four types of geological formations: (1) Chungthang Formation (7.09%), (2) Gorubathan Formation (51.97%), (3) Kanchenjunga Gneiss (24.41%), and (4) Lingtse Gneiss Formation (16.54%), shown in Fig. 4(b). The Chungthang Formation was discovered near Bhusuk and Pam in the northern section of the watershed. The principal rock types in this formation are quartzites, garnet–kyanite–staurolite-bearing biotite schist, calcium silicate rock, graphitic schist, and amphibolite. The Gorubathan Formation was found throughout the central to southern parts of the state, from Gangtok to Singtam and a minor amount of the northwestern half, near Rumtek Monastery, Sikkim, India. Biotite phyllite, chlorite, mica schist, schist, phyllite, and quartzite rock are all found in this formation. The Kanchenjunga Formation was mainly found in the northern and central watershed portions and contains biotite gneiss, kyanite, magnetite, mica schist, and sillimanite granite gneiss. Around the
Gangtok and Tumen Forest block of the watershed, the Lingtse Gneiss Formation, with significant exposures of granite and gneiss, was discovered.

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**Fig. 3.** (a) Topographic Position Index-based Landform (TPI-Landform) Map; (b) Land Use Land Cover (LULC) Map; (c) Terrain Ruggedness Index (TRI) Map; (d) Topographic Wetness Index (TWI) Map.

10. **Elevation:** TIN-based relief map is depicted the elevation spans from 292 m to 4061 m and is divided into nine groups Fig. 4(c) : (1) 292m-710.78m (4.21%), (2) 710.78m-1129.56m (17.47%), (3) 1129.56m-1548.33m (29.48%), (4) 1548.33m-1967.11m (22.97%), (5) 1967.11m-2385.89m (13.51%), (6) 2385.89m-2804.67m (7.28%), (7) 2804.67m-3223.44m (3.50%), (8) 3223.44m-3642.22m (0.97%), and (9) 3642.22m-4061m (0.61%).

11. **Land Use Land Cover (LULC):** The preprocessed LISS-IV images are classified using the Maximum Likelihood Classifier using a supervised classification technique. The land use land cover map with six different classes such as forests (i.e., evergreen, semi-Evergreen, 184.33 km²), scrub forests (13.48 km²), agricultural lands (6.50 km²), built-up (urban) areas (34.75 km²), water bodies (0.68 km²), and others (i.e., barren, sand, and snow, 14.65 km²) for 2020.
are depicted in Fig. 3 (c). Overall accuracy and kappa coefficient values for the classified image are 93.60 percent and 0.81, respectively.

12. Annual Average Frequency of Heavy Rainfall days (AAFHRD): There are five classes of AAFHRD according to the temporal distribution of heavy rainfall (>650 mm): (1) 3-4.4 days (0.88%), (2) 4.4-5.68 days (3.21%), (3) 5.68-6.95 days (6.90%), (4) 6.95-8.22 days (13.46%), and (5) 8.22-10.00 days (75.55%), depicted in Fig 4(d).

The assessment of FFVZs is executed based on the integrated GFAHP method using GIS. The fuzzy pairwise comparison matrix is shown in Table 2. And the weights of the attributes and sub-attributes are depicted in Table 3. After procurement of all the weights for individual attributes and their sub-attributes, Eq. 4 is used to compute the FFVI for the Ranikhola watershed (Fig. 5.). This FFVI map has been reclassified to produce FFVZs. The sample assessment matrix is constructed with the help of modified values from the previous literature. This matrix consists of 5 calibrated weights (including weights assigned for this present study) for 71 sub-attributes (SM: Table 4.). Following
that, grey assessment weight matrices are computed using Eqs. (17) to (25) (SM: Table 5.). The integrated conclusion of the complete evaluation is determined by applying the formula in Eq. 27 (SM: Table 6.). Finally, A single effectiveness value ($EV$) is calculated using Eq. 28. The calculated EV value is 6.4286, which signifies the effectiveness of the flash flood vulnerability map is between moderate and more significant. It is also observed that the acquired LIPs (87%) lie on the High FFVZ.

![Flash Flood Vulnerability Map and Validation Map](image)

**Fig. 5.** Flash Flood Vulnerability Map and Validation Map.

**Table 2.** The Fuzzy Pair-wise Comparison Matrix for Twelve Attributes was used in this study.

<table>
<thead>
<tr>
<th>Attribute</th>
<th>TRI</th>
<th>TWI</th>
<th>Plan</th>
<th>DD</th>
<th>DI</th>
<th>Slope</th>
<th>TPI</th>
<th>Landform</th>
<th>Soil Type</th>
<th>Geology</th>
<th>Elevation</th>
<th>LUL</th>
<th>C</th>
<th>AAF</th>
<th>HR</th>
<th>D</th>
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Table 3. Calculated Weights of Attributes and Sub-attributes for Flash Flood Vulnerability Assessment.

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<thead>
<tr>
<th>Attribute</th>
<th>( W_i )</th>
<th>Sub-attribute</th>
<th>( w_{i}^{k} )</th>
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<tbody>
<tr>
<td>TRI</td>
<td>0.09</td>
<td>0.01-0.38</td>
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</tr>
<tr>
<td></td>
<td></td>
<td>0.38-0.46</td>
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<tr>
<td></td>
<td></td>
<td>0.46-0.52</td>
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<td></td>
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<td>0.52-0.58</td>
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<td></td>
<td>0.58-0.86</td>
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<td>5.54-7.02</td>
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<td>(-65.32)-(-0.05)</td>
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<td>(-0.05)-0.05</td>
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<tr>
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<td>Soil Type</td>
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<td>Coarse loamy Excessive drainage rocky valley fill</td>
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<td>Coarse loamy Excessive drainage stony, fine mixed</td>
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<td>Fine loamy mixed, coarse loamy ever fragmented</td>
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<td>Loamy sketal weathered, coarse loamy rocky</td>
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<td>8.22-10</td>
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**Table 4.** Sensitivity Analysis for Individual Attributes.
Table 4. illustrates the relative percentile variation of FFVZs for individual attributes. The results show that the LULC has the maximum positive influence on high FFVZ, followed by TWI and elevation. In contrast, DD has the most significant detrimental influence, followed by the slope.

5. Conclusions

In this study ALOS-PALSAR DEM (12.5 m resolution) is used to produce primary physiographic and geomorphometric classified images. The spatial results of those attributes can be more accurate by using finer resolution (<5 m) of DEM. The leaf-shaped, small, mountainous Ranikhola watershed has one hydrological station. Therefore, just one hydroclimatic parameter viz, AAFHRD, is used to calculate FFVI. A hybrid model, GFAHP, is proposed to avoid the feebleness of any single MCDM method. The result of the integrated model, GIS, and GFAHP is more productive and acceptable in calculating FFVI and identifying FFVZs.

The FFVI results are grouped into three FFVZs: (1) Low (42%), (2) Moderate (36%), and (3) High (22%). The high FFVZ was discovered in the central, northern, and eastern parts of the watershed. Gangtok, Ranipool, the eastern parts of Genlok, some parts of Rumtek, and Singtam lie on the high FFVZ. The findings of the sensitivity analysis suggest that LULC is the most positive influencing attribute for determining the high FFVZ, while DD is the most negative.

The outcome of this study can be used to adapt mitigation techniques against flash floods and to warn residents of high FFVZ before the water arrival. The GFAHP model can also be applied for flood or flash flood vulnerability mapping in other watersheds, where the hydrological data are limited. Furthermore, flash flood vulnerability maps can be generated using the FFVI, considering changes in components due to a severe occurrence (rapid snow melting in hilltops, urbanization, etc.). Additional criteria might be defined, and the relative weights for the totality of influencing attributes could be re-assessed based on the available data, circumstances, and particularities of the study locations.
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