

PRIORITIZING FLOOD-PRONE AREAS IN WARNA BASIN, INDIA WITH ANALYTIC HIERARCHY PROCESS

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Abstract

Flood events pose significant challenges at the intersection of human needs and hydrological research, necessitating advanced techniques for hazard assessment and mitigation. This study investigates flood susceptibility in the tropical landscapes of the Western Ghats within the Warna watershed, India. Utilizing the Analytical Hierarchy Process (AHP) integrated with Geographic Information System (GIS) tools, the research develops a flash flood susceptibility index. Eleven flood risk parameters were analyzed using remote sensing and GIS to create thematic maps and prioritize areas prone to flash floods. Results indicate that moderate-to-high flood risk zones are predominantly concentrated in the Yennehole catchment area. The Flash Flood Magnitude Index (FFMI) validation confirms the severity of flood hazards in this region, highlighting substantial risks to infrastructure, assets, and human lives. The study also incorporates nine land use and land cover (LULC) characteristics and two flood potential indicators to refine prioritization. Sub-watersheds (SW) were classified into three risk categories: high, moderate, and low. SW5 and SW6 emerged as low-risk areas with high groundwater recharge potential, while SW1 and SW2 were identified as high-risk zones with limited recharge capability. These findings provide a robust framework for stakeholders to develop sustainable watershed management strategies, optimize water resource allocation, and implement effective flood risk mitigation measures, including the placement of water-conservation infrastructure. This research enhances water resource resilience and supports strategic land use planning in flood-prone regions.

Keywords: Analytical Hierarchy Process (AHP); Flash flood susceptibility; Floods; Remote sensing; Tropical humid climate

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Introduction

Flash floods pose significant risks to human lives and ecosystems, often causing extensive damage to communities and infrastructure (Rahman *et al.*, 2021; Taherizadeh *et al.*, 2023). The Swarna Watershed in the Udupi district of Karnataka, India, characterized by its tropical humid climate, has experienced numerous flash flood incidents in recent times, highlighting the need for comprehensive flood identification and management strategies (Vanik *et al.*, 2023). As reported by the Karnataka State Natural Disaster Monitoring Centre (KSNDMC), the Swarna River has breached its banks in multiple locations, resulting in widespread flooding (<https://www.indiatoday.in/india/story/torrential-rain-wreaks-havoc-in-parts-of-karnataka-udupi-worst-hit-1723614-2020-09-20>). These floods have displaced thousands of people, with many seeking refuge in government-aided relief camps supported by organizations such as the National Disaster Response Force (NDRF) and State Disaster Response Force (SDRF) for rescue operations in low-lying areas (<https://www.ibtimes.co.in/udupi-floods-heavy-rainfall-cripples-district-ndrf-deployed-details-828342>). This study aims to address flash flood issues by employing the Analytic Hierarchy Process (AHP) to enhance the precision of flash flood identification within the Swarna Watershed, with particular emphasis on the Yennehole catchment area (Silvestro *et al.*, 2019; Wang *et al.*, 2019).

Flash floods, characterized by their sudden onset, rapid water accumulation, and devastating impact, present challenges in prediction and mitigation, especially at the basin scale and within specific catchments (Spitalar *et al.*, 2014; Ali *et al.*, 2017; Ritter *et al.*, 2020, 2021). Conventional flood identification methods often rely solely on meteorological and hydrological data, potentially overlooking the crucial factors contributing to flash flood events (Silvestro *et al.*, 2019; Ali *et al.*, 2020; Das, 2020; Tan *et al.*, 2024). To address this limitation, this study proposes a comprehensive approach integrating AHP, a robust multi-criteria decision-making tool, to analyze the hydrological dynamics of the watershed (Hammami *et al.*, 2019; Abu El-Magd *et al.*, 2020; Das and Gupta, 2021; Edamo *et al.*, 2022). AHP offers a structured framework for decision-making, enabling the prioritization and weighting of various criteria and factors (Hashemi, 2014; Russo and Camanho, 2015; De Brito and Evers, 2016). In the context of flash flood identification, AHP facilitates the systematic evaluation of multiple variables, allowing the

assignment of relative weights based on their significance (Vaidya and Kumar, 2006; Hammami *et al.*, 2019; Daneshparvar *et al.*, 2022; Gyani *et al.*, 2022). This approach aids in developing a comprehensive flash flood susceptibility model that considers the complex interplay between diverse variables (Santos *et al.*, 2019; Mahato *et al.*, 2021; Shahabi *et al.*, 2021; Islam and Chowdhury, 2024). Recent flash flood events worldwide, such as those in Houston, Texas, and Lyon, France, underscore the urgent need to understand and mitigate flash floods (Ahmadalipour and Moradkhani, 2019; Nkwunonwo *et al.*, 2020; Agonafir *et al.*, 2023). Similarly, devastating occurrences in India, such as the floods in Kerala and Uttarakhand, emphasize the importance of comprehending and managing flash floods within the nation (Tripathi, 2015; Giri and Vats, 2018; Pramanick *et al.*, 2022).

In water resource engineering, flash floods and river (or lowland) floods are two distinct types of flooding, each with unique characteristics, causes, and impacts. Flash floods are sudden and intense events that typically occurring within six hours of heavy rainfall, rapid snowmelt, or dam failures (Patil and Bhagwat, 2022). These floods are characterized by fast-moving water and high velocity, often occurring with little to no warning. They usually develop in areas with steep terrain, such as mountains or narrow valleys, and in urban areas with poor drainage systems (Patil *et al.*, 2024). Flash floods have a short duration, ranging from a few minutes to several hours, but their speed and intensity can cause devastating impacts such as erosion, debris flows, and structural damage. Urban areas are particularly vulnerable to impervious surfaces that prevent rainwater absorption, leading to rapid water accumulation and swift flooding (Chan *et al.*, 2022).

On the other hand, river or lowland floods are gradual floods that occur when rivers overflow their banks due to prolonged or heavy rainfall, snowmelt, or dam release. These floods develop slowly, often over hours to days, and affect larger geographic areas, typically in low-lying regions or floodplains near rivers. River floods are more predictable than flash floods, allowing for advance warnings and preparation. The duration of river floods can extend for days or even weeks, causing widespread inundation of agricultural lands, homes, and infrastructure. Unlike flash floods, which have a high water velocity, river floods involve slower water movement that gradually spreads across a larger area, often leading to long-term waterlogging and damage (Patil and Bhagwat, 2023).

The causes of these floods also vary. In mountainous regions, flash floods are often triggered by intense, short-duration rainfall events, dam or levee breaches, or rapid snowmelt. Flash floods in urban environments can result from poor drainage and impermeable surfaces. River floods, however, are caused by sustained heavy rainfall over an extended period, upstream flooding in a river basin, or seasonal snowmelt, which leads to rising river levels. Coastal areas may experience river flooding as a result of storm surges pushing water inland, causing rivers to backup and overflow.

The destruction of crops and infrastructure exacerbates this situation, resulting in significant economic losses for the affected communities. Despite advancements in flood detection and control, there is a research gap in the formulation of comprehensive frameworks for identifying flash floods in specific watersheds (Kuller *et al.*, 2021; Shahabi *et al.*, 2021). Current methodologies often neglect critical physiographic and hydrogeological factors (Nkwunonwo *et al.*, 2020; Rahman *et al.*, 2021; Chan *et al.*, 2022; Piadeh *et al.*, 2022; Wang *et al.*, 2022; Tang *et al.*, 2023). Moreover, integrated approaches combining AHP with flash flood magnitude indices at the watershed level are lacking (Zhao *et al.*, 2018; Lin *et al.*, 2020; Choudhury *et al.*, 2022; Abdrabo *et al.*, 2023). Addressing this gap is essential for enhancing flash flood

identification and management in specific watersheds. By gaining a thorough understanding of flash flood dynamics in the area, this study aims to identify the vulnerabilities contributing to their occurrence and provide valuable insights for flood risk management, early warning systems, and community resilience efforts. The framework established in this research serves as a robust tool for detecting and managing flash floods in the Swarna Watershed, thereby improving disaster preparedness and response measures.

Study Area

Swarna watershed is situated in the western part of the Western Ghats Mountain range in Karnataka, India, and covers an area of 789.18 km². Its geographical coordinates range from 74° 62' E to 75° 19' E longitude and 13° 13' N to 13° 48' N latitude. Swarna watershed code is designated as 5A3B6. The elevation in the Swarna watershed varies significantly from 0 to 1208 m above MSL. Six rain gauge stations, Mulikar, Ajekar, Kervashe, Karkala, Puttige, and Udupi, were located within the Swarna watershed (Figure 1). A stream gauge station is situated at Yennehole, aiding in the collection of hydrological data to understand the dynamics of water resources within the watershed,

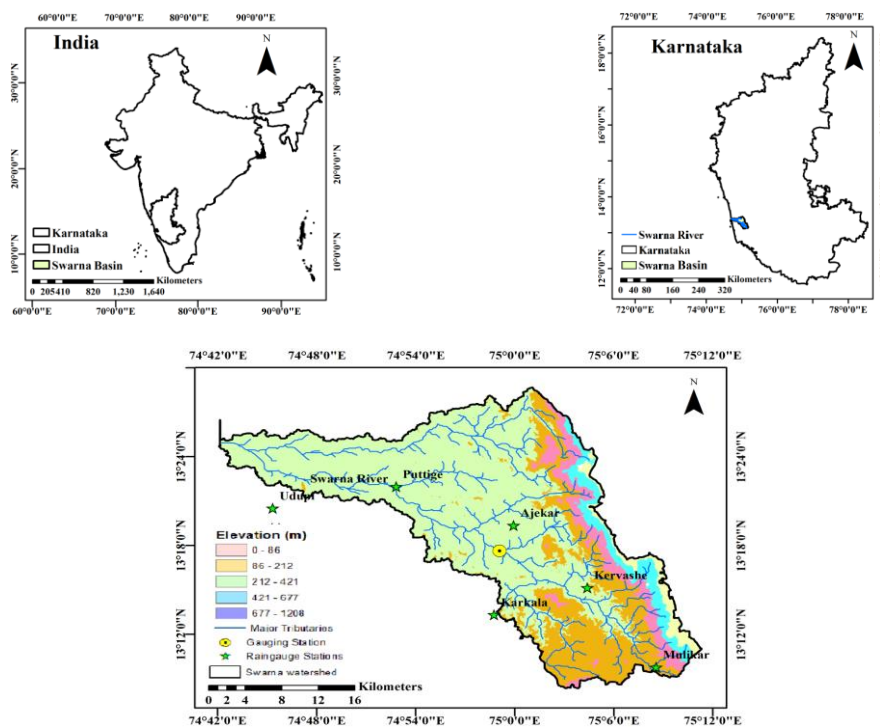


Figure 1. Major tributaries and stream gauge station River Swarna and the locations of rain gauge stations within the Swarna watershed

particularly during extreme events such as floods. The Swarna coastal watershed experiences a tropical monsoon climate characterized by hot and humid conditions. This region receives significant rainfall during the monsoon season, which typically lasts from June to September. The Swarna River experiences a flood season during the Southwest Monsoon, which brings heavy rainfall into the region. The coastal and Western Ghats, where the river originates, receive significant precipitation due to orographic effects. The rainfall in this region can exceed 4,000 mm during the monsoon season. The Swarna River Basin is prone to flash floods due to the steep slopes of the Western Ghats, rapid runoff, and short length of the river system. During intense rainfall events, the river level rises rapidly, which can lead to localized flooding. In 2018 and 2019, the Udupi district, including the Swarna River Basin, experienced significant flooding due to unprecedented monsoon rain. Overflowing rivers and lakes have led to the inundation of agricultural land, roads, and buildings. The Swarna River floodwaters have impacted several low-lying areas around Udupi. The presence of several dams and water management structures, such as check dams and barrages on the Swarna River, play a role in flood dynamics. Downstream flooding can occur when these structures overflow or release water during peak monsoon periods (Patil and Bhagwat, 2019). The Western Ghats cause rapid water flow during heavy rainfall, contributing to a sudden rise in river levels. The expansion of urban areas, particularly around Udupi, has increased surface runoff, reduced natural infiltration, and worsened flood conditions. Many drainage systems in the region are undersized or poorly maintained, leading to backflow and flooding during heavy rainfall events. The hydrology tool was used to divide the watershed into six sub-watersheds in the 5th order, denoted as SW1 to SW6. hydromorphometric

parameters were categorized as morphometric and flood potential indicators.

Methodology

The SRTM DEM with a 30-meter resolution was obtained from the USGS webpage. The projections were based on the Universal Transverse Mercator (UTM), World Geodetic System 1984 (WGS 1984), and Zone 43 North. The DEM was imported and mosaicked, followed by extraction up to the Swarna watershed. Various processes, such as fill, flow direction, flow accumulation, and watershed delineation, have been analyzed using hydrology tools. The flood susceptibility assessment methodology included derived physiographic parameters and spatial maps generated from the digital elevation model, such as the flow accumulation, topographic wetness index, terrain ruggedness index, dissection index, profile curvature, slope, convergence index, and time of concentration. Landsat 8 imagery (downloaded from <https://earthexplorer.usgs.gov/>) was imported into the ArcGIS 10.5 environment. Maximum likelihood supervised classification was performed, classifying nine land use/land cover classes. Field data on soil samples were collected from 14 sampling stations on April 13th and 14, and 2022. Laboratory tests, including sieve analysis, were conducted at each sampling location to categorize soil texture and prepare a soil map. Historical precipitation data spanning 1998 to 2022 were compiled, and the average yearly rainfall for each rain gauge station was computed using a map generated using the Inverse Distance Weighting (IDW) interpolation technique. A comparison matrix is established to assign weights to each criterion based on their importance. Thematic maps were created for all criteria and then ranked using

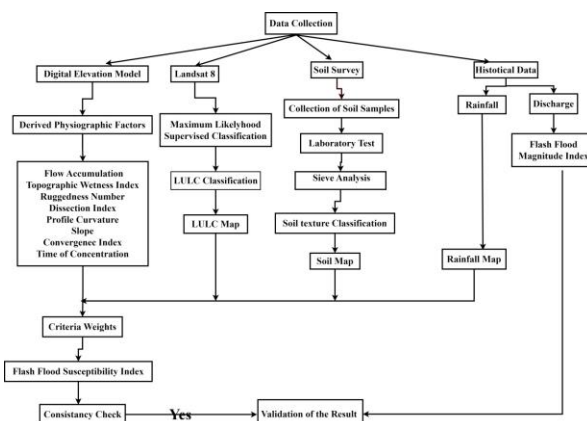


Figure 2. The flowchart illustrates the methodology employed in current research

the Analytic Hierarchy Process (AHP). The reclassified thematic layers, combined with the weighted values of each criterion, were used to produce a flash flood susceptibility index map. The Consistency Ratio was computed to evaluate the reliability of the assigned weights, signifying approval. Subsequently, the accuracy of the flash flood susceptibility index map was assessed and validated using historical stream gauge data from Yennehole using the Flash Flood Magnitude Index. The flowchart is depicted in Figure 2.

Results and Discussion

Derived Physiographic Factors

Derived physiographic factors are landscape characteristics that affect the likelihood and severity of flooding. They are not directly related to water bodies or precipitation but are instead derived from the physical features of the land as discussed below:

Stream Order (u)

Stream order refers to the classification system used to categorize streams based on their hierarchical order within a river network (Strahler, 1957). This principle is fundamental to the study of river morphology and hydrology (Boutaghane *et al.*, 2022). Figure 3 shows the configuration of the dendritic drainage pattern. The highest order in the Swarna watershed is the 6th order and is further divided into six sub-watersheds of the 5th order (Table 1).

Stream Number (Nu)

Stream number denotes the overall quantity of stream segments present within a watershed (Strahler, 1957). The calculation was performed using Equation (1).

$$Nu = Nu1 + Nu2 + Nu3 \cdots + Nun \quad (1)$$

The number of streams fluctuates based on their sequence of occurrence, exhibiting a declining trend as the order of the streams increases (Table 1). The total number of streams was 337 (SW1), 81 (SW2), 153 (SW3), 211 (SW4), 224 (SW5), 480 (SW6), and SRW (2428). Streams with high concentrations are characterized by a well-developed hydrological network, which leads to a larger amount of water being accumulated owing to the increased number of 1st order streams. This facilitates the movement of water from higher to lower elevations, leading to flash flooding and regions with fewer streams (Mahala, 2020).

Stream Length (Lu)

Stream length refers to the distance covered by a stream from its source to its mouth (Horton, 1945). Equation (2) was used to calculate this, as illustrated below:

$$Lu = Lu1 + Lu2 + Lu3 \cdots + Lun \quad (2)$$

The stream lengths SW1 (190.57 km), SW2 (47.43 km), SW3 (114.03 km), and SW4 (137.08 km) are listed in Table 1. In contrast to SW5 (181.40 km) and SW6 (405.73 km), these streams have shorter lengths owing to swift sediment transport and lack of structural complexity. The significant presence of first-order streams in a watershed indicates the prevalence of steep slopes of shorter length in the upper reaches and impermeable lithology, resulting in a reduced infiltration rate and an increased likelihood of flash floods during intense rainfall events (Saha *et al.*, 2022). The number of higher-order streams decreases abruptly from the 3rd order to the 5th order as the stream length increases. However, no consistent pattern

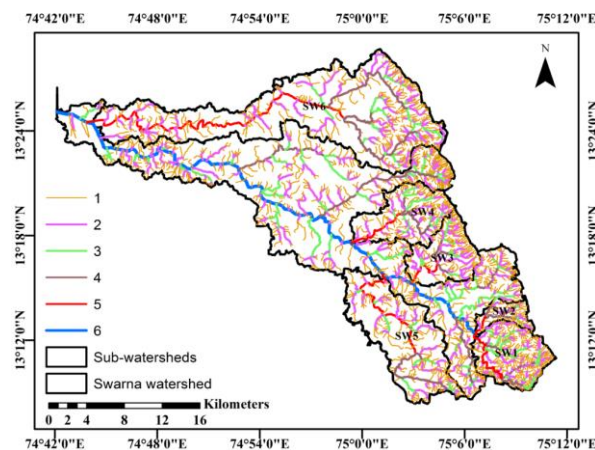


Figure 3. The flowchart illustrates the methodology employed in the current research

Table 1. Descriptive characteristics of the Swarna watershed and its sub-watersheds

Watershed	Stream Order (u)	Number of Streams (Nu)	Stream Length (Km) (Lu)	Mean stream Length (km) (Lsm)	Stream Length Ratio (SLR)	Bifurcation Ratio (Rb)
SRW	1	1856	1039.09	0.56		4.24
	2	438	363.15	0.83	0.35	4.13
	3	106	171.98	1.62	0.47	5.05
	4	21	112.68	5.37	0.66	3.5
	5	6	77.57	12.93	0.69	6
	6	1	60.81	60.81	0.78	
	Total	2428	1825.28	82.12		4.58 (mean)
SW1	1	260	115.11	0.44		4.33
	2	60	36.65	0.61	0.32	4.62
	3	13	20.8	1.6	0.57	4.33
	4	3	9.75	3.25	0.47	3
	5	1	8.26	8.26	0.85	
	Total	337	190.57	14.16		4.07 (mean)
SW2	1	61	27.81	0.46		4.69
	2	13	6.31	0.49	0.23	3.25
	3	4	2.23	0.56	0.35	2
	4	2	8.72	4.36	3.91	2
	5	1	2.35	2.35	0.27	
	Total	81	47.43	8.21		3 (mean)
SW3	1	114	63.08	0.55		4.22
	2	27	30.73	1.14	0.49	3.38
	3	8	8.84	1.11	0.29	2.67
	4	3	5.62	1.87	0.64	3
	5	1	5.76	5.76	1.02	
	Total	153	114.03	10.43		3.32 (mean)
SW4	1	157	78.12	0.5		3.65
	2	43	29	0.67	0.37	5.38
	3	8	14.83	1.85	0.51	4
	4	2	7.87	3.93	0.53	2
	5	1	7.26	7.26	0.92	
	Total	211	137.08	14.22		3.76
SW5	1	172	109.32	0.64		4.53
	2	38	33.17	0.87	0.3	3.8
	3	10	11.77	1.18	0.35	3.33
	4	3	11.35	3.78	0.96	3
	5	1	15.79	15.79	1.39	
	Total	224	181.4	22.26		3.66 (mean)
SW6	1	376	221.07	0.59		4.48
	2	84	89.72	1.07	0.41	5.25
	3	16	27.11	1.69	0.3	5.33
	4	3	30.92	10.31	1.14	3
	5	1	36.92	36.92	1.19	
	Total	480	405.73	50.57		4.51 (mean)

Note: SRW= Swarna River watershed, SW= Sub-watershed

is observed. The reduction in stream numbers with increasing stream order indicates that the tectonically active area has an uneven slope gradient, increasing infiltration rate, and gentler slopes owing to variations in slope and lithology across the Swarna River watershed and sub-watersheds.

Mean Stream Length (Lsm)

The average stream length is determined by measuring the distance from the source to the outlet of the stream (Horton, 1945). Equation (3) was used to perform the calculation as follows:

$$Lsm = (Lu / Nu) \quad (3)$$

It is influenced by various factors such as elevation, slope, and terrain (Sarkar *et al.*, 2020; Víg *et al.*, 2022). The average length of the stream in the SRW is 82.12 km. SW2 (8.21 km), SW3 (10.43 km), SW1 (14.16 km), and SW4 (14.22 km) indicate

steep slopes and rugged terrains. Whereas SW5 (22.26 km) and SW6 (50.57 km) result from gentle slopes and flat terrain leading to extended stream lengths (Table 1).

Stream Length Ratio (SLR)

This stipulates that within a basin, each segment represents the average length of the streams, succeeding order tends to form a direct geometric series (Horton, 1945). The length of the stream increases proportionally as it moves toward higher-order streams (El-Fakharany and Mansour 2021; Portuguese-Maurtua *et al.*, 2023). The transition from one order stream to another is due to changes in topography and slope. Equation (4) was used to perform the calculation.

$$SLR = (Lu/Lu - 1) \quad (4)$$

Where, Lu = Length of each stream order

A higher value indicates regions with mountains and steep slopes and consequently raises the likelihood of water accumulation leading to flooding (Table 1). Conversely, a lower value indicates flatter terrain and lower flood risk.

Bifurcation Ratio (Rb)

It is defined as the ratio of the number of streams of a given order (u) to the next higher order (u+1) (Horton, 1945). This suggests that without strong control of the geological formation, Rb shows only small variations in different regions (Strahler 1957). Equation (5) is utilized for its calculation, as shown below:

$$Rb = (Nu/Nu + 1) \quad (5)$$

Where, Nu= Stream order

This approach enables the assessment of the branching pattern within a drainage network, which

falls between 3.0 to 5.0, suggesting that geological formations have no impact on the basin's drainage pattern (Bharath *et al.*, 2021; Yang *et al.*, 2023). The average bifurcation ratio for the SRW was 4.58. SW1 (4.07), SW2 (3.0), SW3 (3.32), SW4 (3.76), SW5 (3.66), and SW6 (4.51) exhibited high mean bifurcation ratios, confirming that the geological structures had no impact on the watershed (Table 2).

Flood Potential Indicators

The degree of flood hazard for individual sub-watersheds was examined using El Shamy's model (Bhagwat *et al.*, 2011; Pant *et al.*, 2020). The relationship between bifurcation ratio vs. drainage density and stream frequency vs. bifurcation ratio was used to determine the degree of hazard in the sub-watersheds of the Swarna watershed (Figure 4(a, b)). According to El Shamy's model, the food hazard map was classified into three different zones: A, B, and C. Zone A has high flood

Table 2. Morphometric characteristics of Swarna watershed and its sub-watersheds

Sl No	Parameters	SRW	SW1	SW2	SW3	SW4	SW5	SW6
1	Watershed Area (A) (km ²)	789.11	43.3	12.7	38	46.96	85.6	204.6
2	Watershed Perimeter (P)(km)	208	30	21	33	40	58	119
3	Watershed Length (Lb)(km)	60.43	7.78	5.49	8.9	11.27	18.19	37.59
4	Watershed Relief (m)	1208	1098	1110	892	1012	340	860
5	Drainage density (Dd) (m/km ²)	2.31	4.4	3.71	3	2.92	2.12	1.98
6	Stream frequency (Fs) (No./km ²)	3.08	7.78	6.33	4.03	4.49	2.61	2.35
7	Form factor (Ff)	0.22	0.72	0.42	0.48	0.37	0.26	0.14
8	Circularity Ratio (Rc)	0.23	0.60	0.36	0.44	0.37	0.32	0.18
9	Elongation Ratio (Re)	0.52	0.95	0.73	0.78	0.69	0.57	0.43
10	Length of Overland flow (Lo)	0.22	0.11	0.13	0.16	0.17	0.24	0.25
11	Time of concentration (hr) (Tc)	5.14	0.58	0.40	0.72	0.89	2.08	3.42
12	Relief Ratio (Rh)	0.02	0.141	0.202	0.100	0.090	0.019	0.023
13	Ruggedness number (Rn)	2.79	4.83	4.12	2.68	2.96	0.72	1.7

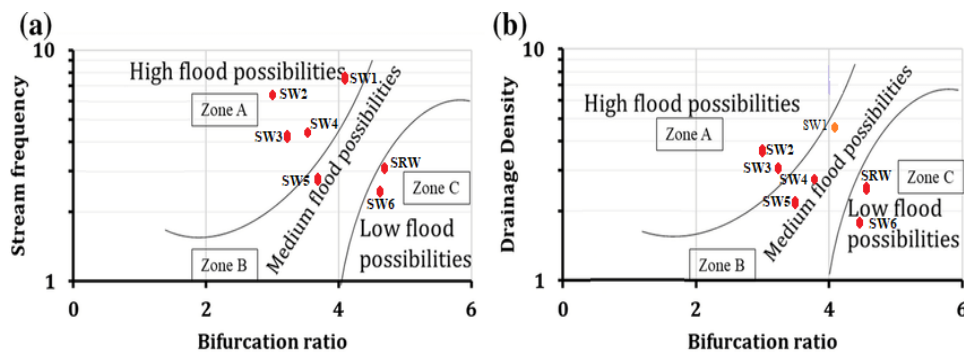


Figure 4. Cross-plot between a) stream frequency vs. bifurcation ratio and b) drainage density vs. bifurcation ratio, indicating flash food possibilities using hydro-morphometric parameters based on El Shamy's model (El Shamy, 1992) in the Swarna watershed and its sub-watersheds

possibilities, Zone B has medium flood possibilities, and Zone C has low flood possibilities. SW1, SW2, SW3, and SW4 exhibit high flood possibilities. SW5 has moderate flood possibilities. SW6 and SRW had low flood possibilities (Figure 4(a)). SW2 and SW3 had high flood probabilities, whereas SW1, SW4, and SW5 had moderate flood possibilities. SRW and SW6 had low flood possibilities (Figure 4(b)). The relationship between the bifurcation ratio and stream frequency SW1 and SW3 has a high risk of flooding; nevertheless, moderate flooding is shown for the same bifurcation ratio vs. drainage density. SW1 and SW4 are a result of the influence of weather. Variations in terrain, the existence of smaller water bodies or streams, or inadequate drainage may all contribute to this intermediate susceptibility. The probability of flooding in certain areas is considerably increased by meteorological conditions such as excessive or extended rainfall periods.

Sub-Watershed Priority Ranking Using

Morphometric Parameters

Prioritization involves hierarchically organizing sub-watersheds according to their flood potential (Bharath *et al.*, 2021). In the Swarna watershed and its sub-watersheds, prioritization was carried out using 13 morphometric parameters to evaluate susceptibility to flood risk. Flood risk is directly influenced by linear and relief parameters, which exhibit a reciprocal relationship with the

aerial parameters. Various factors, including linear, aerial, and relief parameters, contribute to an increased flood risk. The sub-watershed with the lowest rank was assigned to each parameter that was higher, and vice versa. The ranks allocated to all characteristics were averaged to determine the compound values for each sub-watershed. The sub-watersheds with the lowest compound values, SW1 (1.54) and SW2 (1.85), were given the highest priority. Conversely, the sub-watershed with the highest compound value, SW6 (5.69), was given the lowest priority. The first position in the compound ranking is given to SW-1, second to SW2, third to SW3, fourth to SW4, fifth to SW5, and sixth to SW6 (Table 3). Consequently, SW1 and SW2 are among the most significant sub-watersheds, and they possess a higher probability of flooding than SW3, SW4, SW5, and SW6. The importance of the parameters varied across the sub-watersheds of the Swarna watershed, depending on their specific characteristics. Three methods were used to identify sub-basins with varying attributes and prioritize them based on priority levels for subsequent flooding: morphometric analysis, flood potential indicators, and LULC analysis. The lowest compound value was assigned the highest priority (rank 1), and the highest compound value was assigned the lowest priority (rank 5) (Table 4). All the methods show slight changes in priority ranking; therefore, it is reasonable to consider that priority. Based on priority, flood risk levels are classified as high (1-2), moderate (2-4), and low (4-6). SW1 and

Table 3. Ranking and prioritization of morphometric parameters for sub-watersheds of Swarna watershed

Sl No	Parameters	SW1	SW2	SW3	SW4	SW5	SW6
1	Watershed Area (A) (km ²)	3	1	2	4	5	6
2	Watershed Perimeter (P)(km)	2	1	3	4	5	6
3	Watershed Length (Lb)(km)	2	1	3	4	5	6
4	Watershed Relief (m)	2	1	4	3	6	5
5	Drainage density (Dd) (m/km ²)	1	2	3	4	5	6
6	Stream frequency (Fs) (No./km ²)	1	2	4	3	6	5
7	Form factor (Ff)	1	3	2	4	5	6
8	Circularity Ratio (Rc)	1	4	2	3	5	6
9	Elongation Ratio (Re)	1	3	2	4	5	6
10	Length of Overland flow (Lo)	1	2	3	4	5	6
11	Time of concentration (Tc)	2	1	3	4	5	6
12	Relief Ratio (Rh)	2	1	3	4	6	5
13	Ruggedness number (Rn)	1	2	4	3	6	5
	Compound value	1.54	1.85	2.92	3.69	5.31	5.69
	Priority	1	2	3	4	5	6

Table 4. Flash flood risk levels across sub-watersheds within the Swarna watershed

Sl No	Parameters	SW1	SW2	SW3	SW4	SW5	SW6
1	Morphometric Parameters	1	2	3	4	5	6
2	Bifurcation ratio v/s Drainage density	1	2	4	3	5	6
3	Bifurcation ratio v/s Stream frequency	3	1	2	4	5	6
4	Land use/Land cover analysis	2	1	4	3	5	6
	Compound value	1.75	1.5	3.25	3.5	5	6
	Priority	2	1	3	4	5	6
	Flood risk levels	High		Moderate		Low	

SW2 are at a high flood risk (Shekar and Mathew, 2023). SW3 and SW4 were designated as having moderate flood risk, while SW5 and SW6 had low flood risk (Figure 5). This alignment across multiple assessment approaches highlights the importance of prioritizing focused conservation efforts and effective land management approaches within the framework of flood risk.

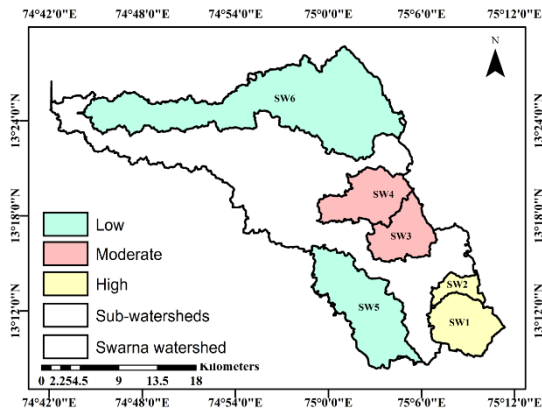


Figure 5. Flood risk levels in sub-watersheds of Swarna watershed

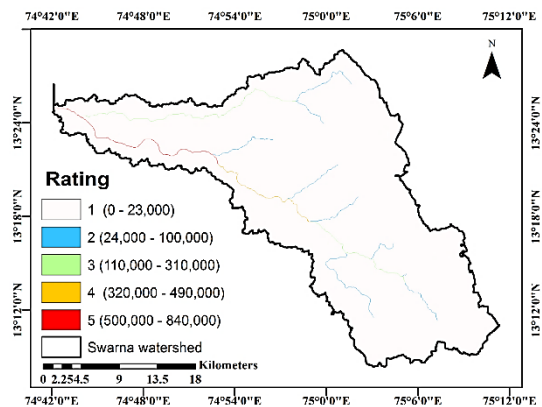


Figure 6. Spatial distribution of flow accumulation in the Swarna watershed

Flow accumulation

Flow accumulation plays a vital role in flood analysis by determining the cumulative upstream flow that contributes to a particular point in the river network (Santos *et al.*, 2019). It calculates the accumulated weight of all the cells flowing into each downslope cell in the output raster (Schäuble *et al.*, 2008). The range of flow accumulation values varied from 0 to 840,000. Classifying the values into distinct categories using the Jenks natural breaks classification method was designed to optimize the arrangement of a set of values into natural classes, resulting in a spatial map illustrating different levels of flood risk (Talha *et al.*, 2019). According to the classification, higher values with higher ranks

prioritize areas that are at a greater risk of flooding, whereas areas with lower values and lower ranks indicate a lower risk (Figure 6).

Dissection Index

The dissection index plays a vital role in assessing the flood risk and quantifying the level of terrain dissection within a watershed. It calculates the watershed's total relative relief relative to its absolute relief. It ranges between 0.0 and 1.0 (Rawat *et al.*, 2021; Saha *et al.*, 2022). It is calculated by using the following equation (6).

$$D_i = \frac{\text{Relative Relief}}{\text{Absolute Relief}} \quad (6)$$

A low dissection index value (close to 0.0) indicates minimal variation in terrain, favoring a flat topography. Such areas are prone to surface water accumulation during heavy rainfall, leading to localized flooding. Conversely, a high dissection index value (close to 1.0) suggests extreme terrain dissection, characterized by steep slopes and rapid water runoff (Mishra and Rai, 2020; Singh and Singh, 2022). This helps identify flood-prone regions within a watershed. Analyzing the spatial distribution of the dissection index across watershed regions with higher dissection index values, such as hilly or mountainous terrain assigned as rank 5, is more susceptible to flash flooding. On the other hand, regions with lower values, such as flat terrain assigned as rank 1, experienced slower and more prolonged inundation during heavy rainfall (Figure 7).

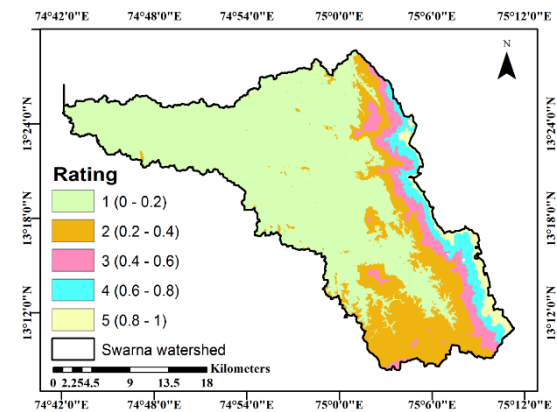


Figure 7. Spatial map of dissection index for floods within the Swarna watershed

Slope

Efficient flood control relies heavily on the significance of slopes for water accumulation. It is defined as an elevation that changes quickly over a given horizontal distance. It refers to the steepness or incline of the land surface and directly affects the

movement of water during heavy rainfall (Cabrera and Lee, 2019). The slope equation (7) is as shown below:

$$\text{Slope} = \frac{\text{Change in elevation}}{\text{Horizontal distance}} \quad (7)$$

Rugged landscapes have varying gradients, with some areas being relatively flat, whereas others have steep slopes (He *et al.*, 2023). A steep slope leads to rapid water movement, resulting in widespread flooding. A gentle slope slows down the flow, allowing water to spread and dissipate, thus reducing the risk of flooding. The spatial context of the slope was categorized and ranked based on the flood risk level in the Swarna watershed. Low flood risk is assigned as rank 1 from 00 to 50, and very high flood risk as rank 5, with slopes ranging from 280 to 690 (Figure 8).

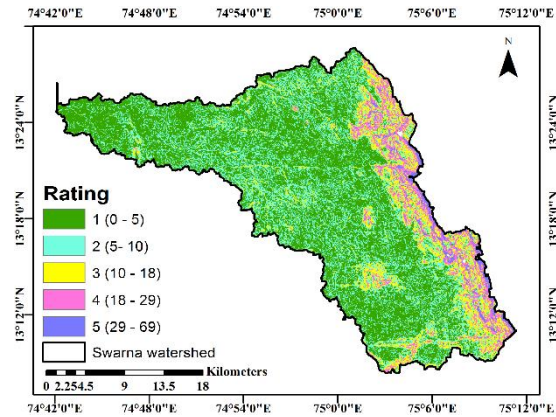


Figure 8. Spatial distribution of slope for floods in the Swarna watershed

Convergence Index

Convergence index is a valuable tool for assessing flood susceptibility in watersheds (Costache *et al.*, 2022). The Convergence Index is a morphometric factor derived from DEM at the same spatial resolution as the slope of the relief. Identifying areas of convergence and divergence offers valuable insights into the topographical characteristics that affect flood risk. A higher value of the convergence index signifies convergent flow, leading to water accumulation and increased flood risk assigned as rank 5. Conversely, a lower value assigned as rank 1 indicates that it facilitates divergent flow, causing water dispersion and reducing flood risk.

Profile Curvature

Profile curvature plays a vital role in comprehending flood dynamics, as it provides insights into the direction of the steepest slope and helps identify landscape features that influence

flood behavior (Ramesh and Iqbal, 2022). This is defined as the curvature of a surface along a specific profile or line. Examining the profile curvature concerning floods, positive values indicate areas where the terrain is convex upward, potentially leading to water accumulation and an increased risk of flooding. Conversely, negative curvature values suggest areas where the terrain is concave upward, allowing water to flow more freely and reducing the risk of flooding (Lee and Kim, 2021). Rank 5 is assigned to a highly convex curvature, which represents the highest risk of flood accumulation, and rank 1 is a highly concave curvature, which poses the lowest risk.

Topographic Wetness Index (TWI)

The compound topographic index (TWI), also known as the steady-state wetness index, is a critical metric used to assess water accumulation potential in areas with varying elevations, particularly concerning flood risk (Sørensen *et al.*, 2006; Saha *et al.*, 2022; Bashir, 2023). It provides valuable insights into the likelihood of flooding within a specific region, and regions with higher TWI values are indicative of greater susceptibility to flooding (Sørensen *et al.*, 2006; Saha *et al.*, 2022; Bashir, 2023). TWI is computed using equation (8),

$$TWI = \ln \left(\frac{\alpha}{\tan \beta} \right) \quad (8)$$

Where, α = upslope contributing area and β = topographic gradient (Slope).

Higher TWI values were assigned a higher rank (rank 5), indicating a greater potential for water accumulation and saturation, making them more prone to flooding, whereas lower TWI values were associated with a lower rank (rank 1), suggesting a lower risk of flooding. This assists in identifying the areas that are most susceptible to flooding.

Topographic Ruggedness number

The Topographic Ruggedness Number is a quantitative measure used to characterize the variation in elevation within a given area. It serves as a numerical measure for evaluating the smoothness or unevenness of a land surface (Lindsay *et al.*, 2019). Higher values of rank 5 indicate heightened vulnerability to soil erosion in the event of flooding, whereas rank 1 of lower values suggests the opposite.

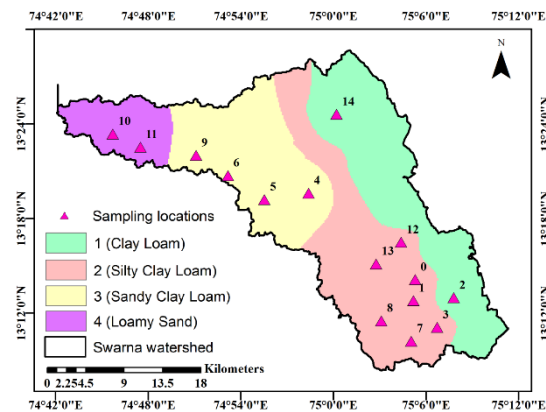
Soil

Soil samples were collected from 14 sampling stations in the Swarna watershed. Sieve analyses were then performed in a laboratory. Based on the

Table 5. Result of sieve analysis at 14 sampling stations within the Swarna watershed

Sl. No	Silt	Clay	Sand	Soil Texture Classification
0	61.82	31.7	6.48	Silty clay loam
1	50.92	32.81	16.27	Silty clay loam
2	38.01	38.46	23.53	Clay loam
3	59.02	37.11	3.87	Silty clay loam
4	19.39	33.18	47.43	Sandy clay loam
5	23.04	25.35	51.61	Sandy clay loam
6	24.77	17.82	57.41	Sandy clay loam
7	53.09	Le 34.98	11.93	Silty clay loam
8	53.01	29.02	17.97	Silty clay loam
9	8.98	22.29	68.73	Sandy clay loam
10	16.52	1.01	82.47	Loam sand
11	10.76	8.59	80.65	Loam sand
12	54.07	37.88	8.05	Silty clay loam
13	59.03	33.45	7.52	Silty clay loam
14	40.04	31.67	28.29	Clay loam

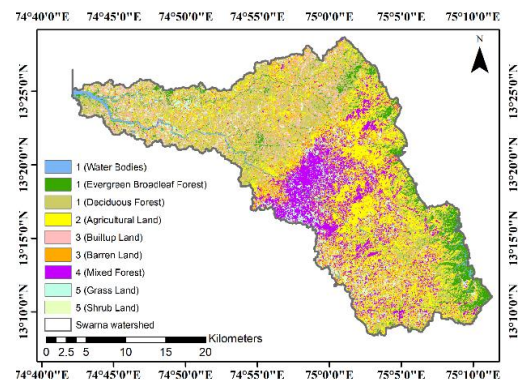
texture classification the soils were grouped as Clay loam, Silty clay loam, Sandy clay loam, and Loamy sand (Table 5). Soil characteristics in a particular area play a crucial role in determining the susceptibility to flooding. Soils with a high proportion of sand tend to facilitate the rapid infiltration of water owing to their porous nature, thereby reducing the risk of surface water accumulation and potential flooding. Clay Loam is assigned with a higher rank of 1 and being less permeable, is associated with a higher risk of flooding. In contrast, Loamy Sand is assigned a lower rank (rank 4) with its greater permeability and is considered to pose a lower risk of flooding, indicating higher resilience against flood hazards (Figure 9).

**Figure 9. Spatial distribution of Soil for the Swarna watershed**

Land use Land cover (LULC)

Land use and land cover in a region has a significant impact on runoff patterns, groundwater quality, and damage caused by flooding events. Vegetated areas promote groundwater recharge by facilitating rainfall infiltration, whereas urbanized areas increase overland flow and flood risk. In the present study, land use and land cover types were

classified with an overall accuracy of 98.25% and a Kappa coefficient of 97.9%. According to the classification, areas with the highest flood risk were assigned a rank of 5. Land use plays a crucial role in hydrological processes, with water bodies, evergreen broadleaf forests, and dense forests being at the lowest risk (rank 1). Grassland and shrubland are at the highest risk (rank 5) because of their higher susceptibility to flood hazards (Figure 10).

**Figure 10. Spatial distribution of land use land cover classification within the Swarna watershed**

Rainfall

Rainfall was selected as one of the major factors influencing the occurrence of flooding. High-intensity rainfall within a short period of time causes flash flooding. Rainfall data were obtained from six meteorological stations in the Swarna watershed and utilized the inverse distance weighting (IDW) interpolation technique to create rainfall maps in the ArcGIS 10.5 environment. The flood risk assessment was determined based on the annual rainfall, which dictates the ranking. Rank 5 signifies the highest risk, indicating significant vulnerability to flooding caused by heavy precipitation. In contrast, rank 1 represents a lower but still noteworthy risk of flooding, necessitating caution and preparedness measures (Figure 11).

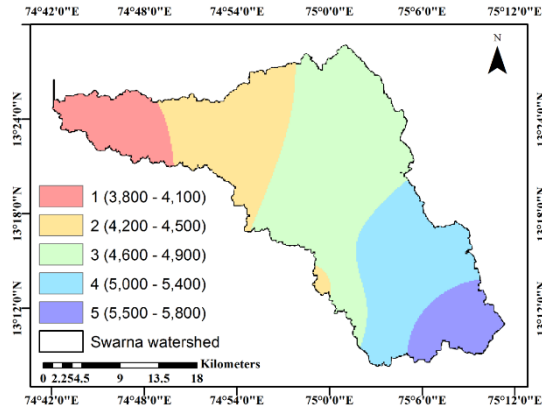


Figure 11. Spatial distribution of the rainfall map for the Swarna River watershed

Time of Concentration

The time of concentration refers to the duration it takes for water to travel from the farthest point in a watershed to a specific location of interest. The following equation was obtained:

$$T_c = 0.0078 * L^{0.77} * S^{0.385} \quad (9)$$

It is an important parameter in hydrology as it helps in estimating the peak flow rate and volume of water expected during a storm event. Considering high flood risk areas, a lower time of concentration is assigned as rank 1, in which water reaches the location of interest relatively quickly. This implies a higher likelihood of experiencing intense and rapid flooding. However, in areas with low flood risk, a higher value of time of concentration assigned as rank 5 suggests that water takes a longer time to travel and results in a lower probability of experiencing significant flooding.

Analytical Hierarchy Process (AHP)

The present investigation employed the Analytical Hierarchy Process (AHP) to ascertain the weights of the individual parameters (Ahmed *et al.*, 2024). In the Analytic Hierarchy Process (AHP), experts play a pivotal role by contributing their specialized knowledge and experience to ensure the accuracy and reliability of the decision-making process. Their expertise is essential for structuring the problem into a clear hierarchy of the overall goal, criteria, sub-criteria, and alternatives, especially in complex fields such as water resource engineering, where multiple factors, such as environmental sustainability, cost, and risk, must be considered. Experts perform pairwise comparisons, evaluating the relative importance of each criterion and alternative using a predefined scale (typically

1-9). These comparisons form the basis of the decision, as the weights or priorities of each element are derived from these expert judgments. Because AHP relies heavily on subjective evaluations, the quality of these judgments is crucial, making the role of experts indispensable for credible outcomes. To ensure consistency and logical coherence in their assessments, a consistency ratio was applied, allowing experts to revise their judgments when inconsistencies were found. In summary, experts drive the entire AHP process by using their insights to balance complex, competing criteria, and ensure that the decision is grounded in a comprehensive understanding of the problem.

The weight assignment process in the Analytic Hierarchy Process (AHP) is central to determining the relative importance of different criteria and alternatives within the decision-making hierarchy. This process begins by structuring the decision problem into levels, typically comprising the overall goal at the top, followed by criteria, sub-criteria, and alternatives at subsequent levels. Once the hierarchy is defined, experts perform pairwise comparisons between elements at each level. For each pair of criteria or alternatives, the expert assesses how much more important or preferable one element is over the other, using a scale ranging from 1 (equal importance) to 9 (extreme preference of one over the other). These comparisons were then recorded in a pairwise comparison matrix, where each matrix element represents the relative importance of one element in comparison to the other. The matrix is normalized by dividing each element by the sum of its columns, and the average of each row provides the approximate weight of the corresponding criterion or alternative. To ensure that the judgments are consistent, AHP calculates the consistency ratio (CR) by comparing the consistency index (CI) with a random consistency index (RI), based on the number of elements in the matrix. If the CR is less than or equal to 0.1, the judgments are considered consistent; otherwise, experts are asked to revise their comparisons. Once the weights of the criteria and alternatives are determined, the final step is to combine these weights, typically by multiplying the local weights of alternatives by the global weights of criteria to obtain an overall ranking of alternatives. This systematic process ensures that subjective expert judgments are translated into objective numerical values that can be used to make well-informed, consistent decisions, making AHP particularly valuable in complex, multi-criteria decision environments, such as Water Resources Engineering.

Table 6. AHP-based Comparative Scale for flood risk assessment

Weights (Intensity of importance)	Definition
1	Equally important
3	Moderate importance
5	Strong importance
7	Very strong importance
9	Extremely important
2,4,6,8	Intermediate preference between the weights

Table 7. Analytical Hierarchy Process-based Pair-wise Comparison Matrix for Parameters of Flood Hazard

Sl. No	Parameters	Flow accumulation	Topographic Wetness Index	Terrain ruggedness number	Dissection Index	Profile Curvature	Slope	Soil	Landuse	Rainfall	Convergence Index	Time of Concentration
1	Flow accumulation	1	9	3	9	3	5	5	5	9	3	9
2	Topographic Wetness Index	0.20	1.80	0.60	1.80	0.60	1.00	1.00	1.00	1.80	0.60	1.80
3	Ruggedness number	0.33	3.00	1.00	3.00	1.00	1.67	1.67	1.67	3.00	1.00	3.00
4	Dissection Index	0.11	1.00	0.33	1.00	0.33	0.56	0.56	0.56	1.00	0.33	1.00
5	Profile Curvature	0.33	3.00	1.00	3.00	1.00	1.67	1.67	1.67	3.00	1.00	3.00
6	Slope	0.20	1.80	0.60	1.80	0.60	1.00	1.00	1.00	1.80	0.60	1.80
7	Soil	0.20	1.80	0.60	1.80	0.60	1.00	1.00	1.00	1.80	0.60	1.80
8	Landuse	0.20	1.80	0.60	1.80	0.60	1.00	1.00	1.00	1.80	0.60	1.80
9	Rainfall	0.11	1.00	0.33	1.00	0.33	0.56	0.56	0.56	1.00	0.33	1.00
10	Convergence Index	0.33	3.00	1.00	3.00	1.00	1.67	1.67	1.67	3.00	1.00	3.00
11	Time of Concentration	0.11	1.00	0.33	1.00	0.33	0.56	0.56	0.56	1.00	0.33	1

Table 8. Flood hazard parameters normalized for the Analytical Hierarchy Process-based assessment of flood

[illegible]

Table 9. Result of sieve analysis at 14 sampling stations within the Swarna watershed

N	1	2	3	4	5	6	7	8	9	10	11
Random Index (RI)	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49	1.51

The existence of numerous interconnected criteria in the study and a decision-making approach that incorporated multiple criteria were implemented. AHP allows for an assessment of the contribution of each factor and aids in addressing the challenges associated with overlaps and identifying relationships among the parameters. Utilizing a comparison scale ranging from 1 to 9, the criteria were prioritized hierarchically based on their relative significance before the decision-making process in the AHP (Table 6). This study employed AHP as a decision-making approach that incorporates multiple criteria. By using a comparison scale and hierarchical structure, the study successfully determined the weights of individual parameters and evaluated their contribution to the overall decision-making process. This approach proved to be effective in addressing the complexities of the study and provided valuable insights into the relationships among different parameters.

In an ongoing investigation, flood susceptibility mapping parameters were derived from a digital elevation model and ranked according to their hierarchical significance. Subsequently, a comparison matrix was created to allocate weights to these parameters. The level of consistency was assessed using the Consistency Ratio. The final flash flood hazard susceptibility index map (FFSI) was computed by integrating the weights of each parameter. Table 7 shows the comparison matrix of the 11 parameters, with diagonal values of 1. The values in the rows indicate the relative importance of these two parameters. For example, in Table 7, the first row demonstrates the significance of flow accumulation in comparison to the other parameters.

Flow accumulation was moderately more important than the terrain ruggedness index (TRI), profile curvature, and convergence index in influencing floods; hence, a value of three was assigned. Flow accumulation was notably stronger than the topographic wetness index, Slope, Soil, and Land use land cover, with a value of 5. Flow accumulation was significantly more crucial than the topographic ruggedness index, dissection index, rainfall, and time of concentration, with values of 9. Table 8 shows the normalized values of the parameters along with their criteria weights.

Consistency Ratio (CR)

The consistency of the AHP eigenvector matrix must be assessed, as it has been created. The following equation is used to determine the necessary degree of consistency:

$$CR = \left(\frac{CI}{RI} \right) \quad (10)$$

where CR = consistency ratio; CI= consistency index; RI = random index.

The values of RI are listed in Table 9. These values depend on the number of criteria used. In this study the criteria are eleven and as a result the RI = 1.51.

The consistency Index (CI) was calculated using the following formula.

$$CI = \frac{\lambda_{max} - n}{n - 1} \quad (11)$$

λ_{max} = Principal Eigenvalue; n = Total number of comparisons

The maximum eigenvalue of the comparison matrix, denoted as λ_{max} , and number of criteria, denoted as n, were utilized in the current investigation. The computed λ_{max} value was 11.80, with n = 11. Following the division of CI by RI, the Consistency Ratio (CR) was calculated as 0.08, which is less than 0.1, thereby leading to acceptance of the obtained outcome (Ahmed *et al.* 2024).

Flash Flood Susceptibility Index (FFSI)

Thematic maps for each parameter were created and reorganized based on the assigned ranks using AHP. The reorganized thematic layers, along with the weighted values of each parameter, were used to develop the flash flood susceptibility index. The FFSI map was produced in ArcGIS 10.5 software through the “raster calculator” tool (Al-rizouq *et al.*, 2024). The formula for calculating FFSI is presented in Equation (12).

$$FFSI = \sum_{i=1}^n r_i * w_i \quad (12)$$

$$FFSI = F * w_F + T * w_T + R * w_R + D * w_D + P * w_P + S * w_S + C * w_C + R * w_{Ra} + L * w_L + S * w_S + T * w_{Ti}$$

Where,

ri = the rating of the parameter in each point;
wi = the weight of each parameter; n = the number of criteria; F = Flow accumulation, T = Topographic Wetness Index R = Terrain Ruggedness Number, D = Dissection Index, P = Profile curvature, So = Slope, C = Convergence index, Ra = Rainfall, L = Landuse Landcover, So = Soil, Ti = Time of concentration

The present study was an attempt to identify flash flood susceptibility zones within the Swarna watershed using the Analytical Hierarchy Process (AHP) in GIS. Eleven parameters closely related to flood susceptibility were considered when creating the weighted thematic maps and composite, which in turn produced the final map of the flash flood susceptibility index (FFSI). They were grouped into five classes based on their ranks. 1st rank was assigned to low flood risk, 2nd rank was assigned to low flood risk, 3rd rank was assigned to moderate flood risk, 4th rank was assigned to high flood risk and 5th rank was assigned to very high flood risk (Figure 12). The higher values indicating a higher susceptibility to flooding assigned as rank 5, means that areas with a higher flood susceptibility index are more likely to experience flooding, while areas with a lower index are less likely to be affected by floods assigned as rank 1. Despite its smaller size, the Yennehole gauging station suggests that a considerable part is susceptible to flooding, with significant concentrations of high flood risk spread throughout the region, and very high flood risk continued in the low-lying areas downstream of the Swarna watershed.

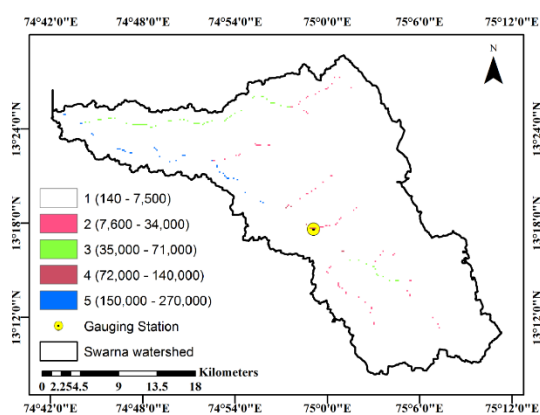


Figure 12. Spatial distribution of flash flood susceptibility index (FFSI) in the Swarna watershed

Flash Flood Magnitude Index

Flash Flood Magnitude Index is the ratio of the peak discharge to the mean annual discharge. This

is more important than the absolute flood discharge of a river for geomorphic changes (Ghosh and Guchhait, 2016; Karim *et al.*, 2017). The Flash-Flood Magnitude Index (FFMI) was used to analyze the variation in upstream and downstream floods. It was calculated based on the standard deviation of the logarithm of the annual maximum discharge. The decadal basis of FFMI was calculated using Equation (13), as shown below (Karim *et al.*, 2017).

$$FFMI = \sqrt{\frac{\sum X^2}{N-1}} \quad (13)$$

Where, $X = \log Q_{\max} - \log Q_{\text{mean}}$, $Q_{\max}$ = annual maximum discharge, Q_{mean} = mean annual discharge, and N = number of years recorded.

FFMI is a valuable tool for assessing and mitigating the impacts of extreme flash flood events in a watershed. The FFMI was used to measure the risk of flash floods and geomorphic changes in the Swarna watershed based on peak discharge during a flood event. The FFMI is exponentially ($Y_c = 1.0388X^{0.5567}$) related to the deviation from the mean discharge to the extreme peak value, and a high deviation corresponds to a high FFMI and extreme flash floods. This index is closer to 1.0, indicating a high degree of flash flood episodes with some geomorphic changes within the basin. The Swarna watershed has an average FFMI of 1.24, which is higher than the global average of 0.278, indicating a significant risk of flash floods in the downstream area (Figure 13).

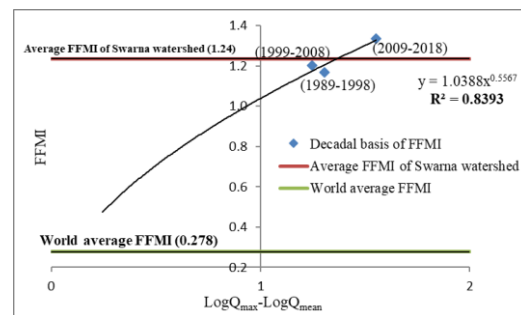


Figure 13. Deviation from the mean discharge compared to the extreme peak discharge for high-magnitude flash floods in the Swarna watershed and the global average FFMI

The response effectively confirms the analysis by exploring the factors that contribute to the increased flood risk in the Yennehole catchment, emphasizing the topographical features and geological composition to accelerate water flow and limit water absorption, resulting in higher flash

flood susceptibility downstream. Furthermore, the use of the Flash Flood Magnitude Index (FFMI) to evaluate flash flood risk adds a quantitative aspect to the analysis, enhancing its validation. Furthermore, the discussion on the above-average FFMI of the Swarna River and its impact on downstream flash flood risks strengthens the validation process. By emphasizing the importance of recognizing localized flood risk variations, this aligns with the original analysis focusing on localized flood risk assessment for effective flash flood management.

Conclusion

Hydromorphometric analysis for flood potential assessment in the Swarna Watershed, Karnataka, India, provides crucial insights into managing mountain hydrology in coastal regions prone to flooding. Using Geographic Information Systems (GIS) and remote sensing techniques, this study prioritizes sub-watersheds based on flood potential, identifying SW1 and SW2 as key areas because of their high bifurcation ratio and drainage density, which are both essential indicators of flood susceptibility. Additionally, the integration of land use and land cover analysis enhances the understanding of the influence of terrain on water flow dynamics, particularly in areas experiencing increasing rainfall intensity. This comprehensive approach is vital for developing effective flood mitigation strategies, particularly in regions such as the Swarna watershed, which faces heightened risks from intensifying precipitation trends. The study also incorporates the Analytic Hierarchy Process (AHP) to assign criteria weights and ranks 11 hydrogeomorphological parameters affecting flood risk, producing a detailed flash flood susceptibility index. The Yennehole catchment area and downstream regions were identified as highly vulnerable to flash floods, with a Flash Flood Magnitude Index (FFMI) of 1.24, significantly surpassing the global average. By layering thematic data within a GIS framework, this study highlights the complex interplay of topographic, geological, and hydrological factors that contribute to flash flood risks, providing valuable data for decision-makers. However, the study also acknowledges limitations such as the reliance on historical data and the absence of future climate impacts and socioeconomic factors, underscoring the need for ongoing research and data collection. Addressing these gaps could improve flood risk management strategies and ensure the safety and sustainability of communities in flood-prone coastal regions. The collaborative and integrative nature of this research emphasizes the

need for holistic water management approaches to effectively mitigate the growing threats of floods.

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