

Assessing Flood Susceptibility of Sub-basins in Kapisa Using HEC-HMS Hydrological Modeling, AHP and ArcGIS Pro

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ABSTRACT

Flood susceptibility assessment in ungauged mountainous catchments is challenging because streamflow observations are limited and conventional approaches may rely mainly on static topographic and environmental characteristics without explicitly accounting for hydrological response. This study presents an event-based flood susceptibility prioritization framework that integrates HEC-HMS 4.12 hydrological modeling with Analytic Hierarchy Process (AHP) spatial analysis in ArcGIS Pro to assess and prioritize relative flood susceptibility across 18 sub-basins in Kapisa Province, Afghanistan. A seven-day storm event from April 10–17, 2024, was simulated using GPM IMERG V07 satellite precipitation data. Marginal peak discharge from HEC-HMS sub-basin elimination analysis, together with Soil Conservation Service Curve Number (SCS-CN) and terrain slope, was incorporated into the AHP-based Flood Susceptibility Index. The AHP-Online System assigned weights of 64.8% to marginal peak discharge response (n_{HMS}), 23.0% to composite SCS-CN (n_{CN}), and 12.2% to terrain slope (n_{Slope}). Results demonstrated substantial differences in hydrological response among the 18 sub-basins. Subbasin-3 produced the highest marginal peak discharge of 140.9 m³/s, while Subbasin-22 generated the largest marginal runoff volume contribution of $5,450.2 \times 10^3$ m³. For this study, Subbasin-22 and Subbasin-2 were classified as very highly susceptible, while Subbasin-3, Subbasin-8, Subbasin-10, Subbasin-14, Subbasin-18, and Subbasin-19 were highly susceptible. Their combined runoff volume contributions represented 23.2% of total runoff volume. The framework provides a practical screening tool for sub-basin prioritization, monitoring, field investigation, and management in data-scarce mountainous regions, but should be interpreted as relative prioritization for the investigated event rather than absolute long-term flood risk.

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INTRODUCTION

Recurrent flash floods and river floods are major hazards for the mountainous catchments of South Asia. Afghanistan is particularly susceptible to these hazards due to its rugged topography, limited meteorological monitoring stations and poor early warning systems (Ahmad et al., 2024a; Ikram et al., 2024a; Mushwani et al., 2025a). In Kapisa Province, steep sub-basins are often affected by high-altitude snowmelt and spring rainstorms, resulting in frequent and severe seasonal flooding. Such flood events wash away agricultural land, ruin

rural dwellings and road networks, and lead to more economic hardship in rural communities (Ikram et al., 2024b; Mushwani et al., 2024a). Because ground observations are scarce, identifying which sub-basins have the highest flood susceptibility during extreme rainfall events is an essential first step for targeted disaster management and resource allocation.

Researchers commonly use Multi-Criteria Decision Analysis (MCDA), hydro-morphometric parameters and statistical models for mapping flood susceptibility. The Analytic Hierarchy Process (AHP) and Fuzzy AHP offer structured ways to evaluate parameters such as slope, elevation, drainage density, land cover, and soil hydrologic groups (Ghosh & Gope, 2021a; Vilasan & Kapse, 2022a). The integration of AHP and Geographic Information Systems (GIS) provides a practical way to map flood susceptibility across catchments of varying scales (Malla & Ohgushi, 2024a; Mushwani et al., 2024b; Tariq et al., 2022a). Comparative studies matching AHP against frequency ratio and maximum entropy models show that multi-criteria decision methods can identify high-susceptibility sub-watersheds even when streamflow measurements are missing (Malla & Ohgushi, 2024a; Qasimi et al., 2024a). Morphometric analysis—focusing on channel geometry, stream order, and basin shape—further clarifies which sub-basins respond quickly to sudden rainfall (Ghosh & Gope, 2021b).

Alongside spatial decision models, semi-distributed hydrological software simulates surface runoff volumes and peak discharge hydrographs. The Hydrologic Modeling System (HEC-HMS) of the Hydrologic Engineering Center has been widely used to simulate event-based rainfall-runoff processes in complex terrain (Hydrologic Engineering Center, 2023a, 2023d). When combined with ArcGIS Pro (Environmental Systems Research Institute, 2023a), HEC-HMS allows researchers to extract sub-basin features, calculate SCS curve numbers, and derive time-of-concentration metrics (Hydrologic Engineering Center, 2023a; Islam & Meng, 2022a). Satellite observations—such as GPM IMERG precipitation data (Huffman et al., 2023a), NASA POWER meteorology (National Aeronautics and Space Administration, 2024a), and Sentinel-1 SAR imagery—make it possible to parameterize remote, ungauged basins accurately (Islam & Meng, 2022a; Pandey et al., 2022a). Combining satellite precipitation with GIS tools and HEC-HMS routing allows researchers to estimate peak runoff across unmonitored catchments.

Despite the growing application of flood susceptibility models, two important gaps remain. First, most spatial hazard assessments in Afghanistan rely on static indices or probabilistic approaches that do not account for runoff dynamics—specifically, simulated peak discharge and flood volume (Ikram et al., 2024c; Qasimi et al., 2024a). Second, hydrological studies using HEC-HMS typically generate hydrographs in isolation, without combining peak flow outputs into a multi-criteria decision matrix for regional planning (Ghosh & Gope, 2021b; Hydrologic Engineering Center, 2023a). In Kapisa Province, where hydrometeorological ground stations are extremely scarce and early warning infrastructure is underdeveloped (Ahmad et al., 2024a; Mushwani et al., 2025a), few studies have evaluated sub-basin prioritization. To our knowledge, no previous work in Afghanistan has combined

HEC-HMS-derived peak discharge with spatial multi-criteria analysis for sub-basin prioritization.

To address these gaps, HEC-HMS runoff simulations were integrated with AHP-based spatial analysis to assess event-based flood susceptibility across the 18 sub-basins of Kapisa Province. Our work had three main objectives: (1) simulate peak runoff hydrographs across Kapisa's sub-basins for design storm events using HEC-HMS (Hydrologic Engineering Center, 2023a); (2) evaluate hydro-environmental factors (slope, elevation, drainage density, land cover, soil hydrologic groups, rainfall, and simulated peak flow) using AHP criteria weighting; and (3) construct a Flood Susceptibility Index (FSI) to classify sub-basins into prioritized susceptibility tiers for the investigated event. The analysis addressed three specific questions:

1. How do the Kapisa sub-basins differ in peak flow during extreme rainfall?
2. How do their topographic and hydrological characteristics shape flood susceptibility?
3. which sub-basins should be prioritized for mitigation efforts?

Our approach differs from previous assessments by including HEC-HMS peak discharge in the AHP analysis (Goepel, 2018). This allows the sub-basins to be ranked using both their physical characteristics and simulated runoff response. The resulting ranking can help identify areas where flood-mitigation measures should receive priority. The resulting susceptibility classes represent event-specific prioritization for the investigated storm rather than absolute long-term flood risk. The main objective of this study is;

- To assess and rank the flood susceptibility of sub-basins in Kapisa Province using HEC-HMS, AHP, and ArcGIS Pro, so that high-risk areas can be prioritized for flood management.

METHODS AND MATERIALS

Study Area

Kapisa Province is located in eastern Afghanistan, approximately 70 km northeast of Kabul, between latitudes 34°50' N to 35°10' N and longitudes 69°30' E to 69°50' E. The province covers an area of approximately 1,842 km², with elevations ranging from about 1,200 m in the river valleys to over 4,200 m in the Hindu Kush mountain ranges. The terrain is characterized by steep slopes, narrow valleys, and rugged mountainous topography Figure 1.

The study area experiences a continental climate with cold winters and warm summers. Precipitation occurs primarily during two seasons: winter snowfall in the higher elevations and spring rainfall from March to May. Annual precipitation varies from approximately 400-600 mm in the valleys to over 1,000 mm in the mountains. The major drainage system is the Panjshir River. The 18 sub-basins analyzed in this study drain into this river system.

The geology consists primarily of metamorphic rocks, including schist, gneiss, and marble. Soils are generally shallow, coarse-textured, and have low infiltration capacities.

Land use is dominated by natural vegetation (approximately 70%), with agriculture concentrated in valley bottoms.

Historically, Kapisa has experienced frequent flood events, with major floods recorded in 2005, 2007, 2010, 2015, and 2024. The April 2024 event was particularly severe. The lack of hydrometeorological monitoring stations means that flood risk assessment must rely on satellite observations and hydrological modeling.

Research Framework

To rank event-based flood susceptibility in Kapisa Province's 18 sub-basins, we combined HEC-HMS 4.12 runoff simulations with spatial MCDA (Ikram et al., 2024a; Mushwani et al., 2025a). HEC-HMS simulated peak discharge and runoff volume, while the Sub-basin Elimination Method quantified each sub-basin's marginal hydrological response (Hydrologic Engineering Center, 2023b, 2023e; Qasimi et al., 2024b). Pairwise comparison matrices for criteria weighting were evaluated using the AHP Online System, and the resulting priority weights were integrated into ArcGIS Pro (Environmental Systems Research Institute, 2023b) for spatial susceptibility modeling (Ghosh & Gope, 2021c; Vilasan & Kapse, 2022b). All spatial rasters were projected to the WGS 1984 UTM Zone 42N coordinate reference system.

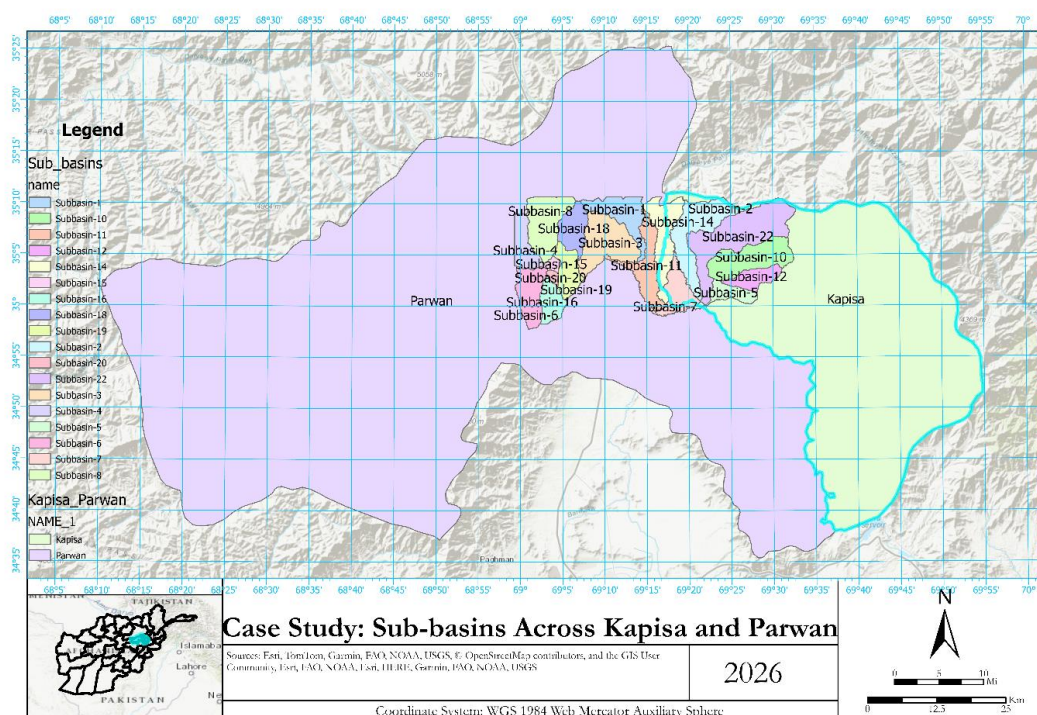


Figure 1. Study Area (Sub-Basins in Kapisa Province)

To examine watershed responses under heavy precipitation, a continuous seven-day rainfall period from April 10, 2024 (12:00 PM) to April 17, 2024 (11:00 AM) was simulated across all

sub-basins using the same rainfall input and model configuration (Ahmad et al., 2024b; National Aeronautics and Space Administration, 2024b). This event was selected based on

historical rainfall analysis showing it ranked among the top 5% of events in the 2001-2024 record, with total precipitation of 78.4 mm and maximum intensity of 12.6 mm/h.

Data Acquisition and Geospatial Processing

Four types of spatial data: satellite precipitation, elevation, land cover, and soil. For terrain representation, we used a 30-m SRTM DEM (Global 1-arc-second V003) acquired from the USGS Earth Explorer platform. The DEM was first imported into WMS for initial terrain processing (Tariq et al., 2022b). The processed elevation raster was subsequently imported into HEC-HMS 4.12 for watershed preprocessing, including sink filling, generation of flow-direction and flow-accumulation grids, stream-network delineation, identification of the terminal outlet (Sink-1), and extraction of sub-basin boundaries as vector shapefiles. The delineation procedure produced 18 sub-basins. The total GIS catchment area is 1,246.55 km², of which 849.6 km² forms the contributing drainage area. The remaining 397 km² represents non-contributing areas (closed basins and internal drainage).

hourly precipitation data (0.1° × 0.1°) from the GPM IMERG Final Run V07 dataset (GPM_3IMERGHH V07) for April 10–17, 2024, using Google Earth Engine (Huffman et al., 2023b; Islam & Meng, 2022b; Pandey et al., 2022b). In addition, the 10-m ESA World Cover v200 land-cover dataset, derived from Sentinel-1 and Sentinel-2 observations, and FAO/HWSD v1.2 Soil Hydrologic Group (HSG) data were combined in GEE to derive spatially distributed Soil Conservation Service Curve Number (SCS-CN) (Malla & Ohgushi, 2024b; National Aeronautics and Space Administration, 2024b). The resulting composite CN raster was exported as a 30-m GeoTIFF for hydrological parameterization. The CN values were assigned using standard USDA-NRCS tables under AMC-II conditions. The ESA WorldCover classes were converted to hydrologic land-use classes, and HSG classes were assigned based on FAO/HWSD soil data.

Hydrological Modeling in HEC-HMS

Rainfall-runoff transformation was simulated using the Gridded SCS Curve Number loss method in HEC-HMS 4.12 (Hydrologic Engineering Center, 2023c). The potential maximum soil retention (S , in inches) was calculated from the composite CN raster using:

$$S = \left(\frac{1000}{CN} \right) - 10 \quad (3)$$

Sub-basin travel-time parameters, including the time of concentration (T_c , hours) and time lag (T_{lag} , hours), were calculated using SCS empirical equations:

$$T_c = \frac{[(S+1)^{0.7} \times L^{0.8}]}{[1140 \times Y^{0.5}]} \quad (4)$$

$$T_{lag} = 0.6 \times T_c \quad (5)$$

Where S is potential maximum retention (inches), L is hydraulic flow length along the longest flow path (feet), and Y is average sub-basin slope (percent). Net excess rainfall was transformed into direct surface-runoff hydrographs using the SCS Unit Hydrograph method (Hydrologic Engineering Center, 2023c).

Streamflow routing through Reach-1 to Reach-10 was simulated using the Muskingum routing method (Hydrologic Engineering Center, 2023c). Because continuous streamflow observations were unavailable for dynamic channel calibration, routing parameters ($K = 0.5$, $X = 0.2$) were adopted based on estimated reach travel times and ungauged-basin modeling guidance (Hydrologic Engineering Center, 2023c).

Sub-basin Contribution Analysis via the Sub-basin Elimination Method

To quantify the marginal hydrological effect of each sub-basin on downstream peak discharge and surface runoff at the main outlet (Sink-1), the Sub-basin Elimination Method was implemented (Mushwani et al., 2024a, 2025b; Qasimi et al., 2024c).

First, a baseline HEC-HMS simulation was performed with all 18 delineated sub-basins active. The resulting peak discharge and total runoff volume at Sink-1 were recorded as Q_{baseline} and V_{baseline} , respectively.

Each sub-basin was subsequently eliminated individually in a separate simulation by disabling its loss and transform components while keeping the rainfall input, remaining sub-basins, channel-routing structure, and all other model parameters unchanged. Following each simulation, the peak discharge and total runoff volume at Sink-1 were recorded. The marginal effect of sub-basin i was calculated as:

$$Q_{\text{net},i} = Q_{\text{baseline}} - Q_{\text{without } i} \quad (6)$$

$$V_{\text{net},i} = V_{\text{baseline}} - V_{\text{without } i} \quad (7)$$

Where $Q_{\text{without } i}$ and $V_{\text{without } i}$ represent the peak discharge (m³/s) and total surface-runoff volume (m³), respectively, at Sink-1 after sub-basin i was eliminated. Q_{net} and V_{net} represent the marginal changes in downstream peak discharge and runoff volume associated with the removal of sub-basin i , not the physical contribution fraction, as routing and hydrograph synchronization effects are captured by the elimination method.

The elimination procedure was repeated for all 18 sub-basins, producing one comparable $Q_{\text{net } i}$ and $V_{\text{net } i}$ value for each sub-basin. A minimum contributing drainage-area threshold of 0.5 km² was used during stream-network delineation to define headwater channels.

For spatial integration, the $Q_{\text{net } i}$ values were normalized across the 18 sub-basins to a 0–1 scale using linear min-max normalization. The normalized values were then joined to the corresponding sub-basin polygons in ArcGIS Pro and rasterized to a 30-m grid with the same cell size, spatial extent, and coordinate reference system as the CN and slope datasets. This produced the normalized HEC-HMS criterion, n_{HMS} , used in the subsequent AHP-based Flood Susceptibility Index (FSI). Although $V_{\text{net } i}$ was retained for analysis of volumetric runoff response, it was not included as a separate AHP criterion because the final prioritization focused on the marginal downstream peak-discharge response.

Spatial Multi-Criteria Prioritization Using AHP and GIS

The Flood Susceptibility Index (FSI) incorporated three criteria: normalized HEC-HMS marginal peak-discharge response (n_{HMS} , Crit-1), terrain slope (n_{slope} , Crit-2), and composite SCS Curve Number (n_{CN} , Crit-3) (Environmental Systems Research Institute, 2023b; Ghosh &

Gope, 2021c; Malla & Ohgushi, 2024b; Vilasan & Kapse, 2022b). Although CN and slope-related travel-time characteristics partly influence the HEC-HMS response, n_{CN} and n_{Slope} were retained as separate criteria to distinguish local runoff-generation potential and terrain sensitivity from the marginal downstream peak-discharge response obtained through the Sub-basin Elimination Method. To address potential double-counting, a sensitivity analysis was conducted comparing FSI rankings using different criteria combinations (n_{HMS} alone, n_{HMS+CN} , $n_{HMS+slope}$, all three).

Pairwise comparisons were established using Saaty's 9-point fundamental scale and evaluated using the AHP Online System (Goepel, 2018) to derive normalized priority weights (Table 1). The AHP-OS evaluation of the decision matrix yielded priority weights of 64.8% for Crit-1 (n_{HMS}), 12.2% for Crit-2 (n_{Slope}), and 23.0% for Crit-3 (n_{CN}). The resulting pairwise comparison matrix produced a principal eigenvalue (λ_{max}) of 3.004, a Consistency Index (CI) of 0.002, and a Consistency Ratio (CR) of 0.004 (0.4%), indicating a high level of consistency and satisfying the commonly accepted $CR < 0.10$ criterion ((Ghosh & Gope, 2021c; Vilasan & Kapse, 2022b).

Table 1. AHP Pairwise Comparison Decision Matrix and Derived Priority Weights

AHP Criterion	n_{HMS} (Crit-1)	n_{Slope} (Crit-2)	n_{CN} (Crit-3)	Derived Prioritized Weight (w-i)	Rank
n_{HMS} (Crit-1)	1.000	5.000	3.000	(64.8%)	1
n_{Slope} (Crit-2)	0.200	1.000	0.500	(12.2%)	3
n_{CN} (Crit-3)	0.333	2.000	1.000	(23.0%)	2

Before weighted overlay, each criterion was normalized to a 0–1 scale using linear min-max normalization:

$$nX_i = (X_i - X_{min}) / (X_{max} - X_{min}) \quad (8)$$

where nX_i is the normalized value, X_i is the original criterion value, and X_{min} and X_{max} are the minimum and maximum values within the study basin, respectively. Higher normalized values represented greater flood susceptibility for all three criteria.

The priority weights derived from AHP-OS were imported into ArcGIS Pro and applied through a weighted raster overlay to calculate the cell-based Flood Susceptibility Index:

$$FSI_{cell} = (0.648 \times n_{HMS}) + (0.230 \times n_{CN}) + (0.122 \times n_{Slope}) \quad (9)$$

where n_{HMS} , n_{CN} , and n_{Slope} represent the normalized HEC-HMS marginal peak-discharge response, SCS-CN, and terrain-slope layers, respectively.

To obtain a single susceptibility score for each sub-basin, the spatial mean of FSI_{cell} was extracted within each sub-basin boundary using the Zonal Statistics (Zonal Mean) function in ArcGIS Pro Spatial Analyst. The resulting FSI_{mean} values were used to rank the 18 sub-basins. They were subsequently classified into five relative susceptibility categories—Very Low, Low, Moderate, High, and Very High—using the Natural Breaks (Jenks) optimization method ((Ghosh & Gope, 2021c; Mushwani et al., 2025b; Tariq et al., 2022b). To test the

sensitivity of classification, alternative methods (quantiles and equal intervals) were also evaluated, and high and very high categories remained stable.

Uncertainty and sensitivity assessment

A quantitative uncertainty assessment was conducted to evaluate the sensitivity of sub-basin rankings to key model parameters. The following parameters were varied: SCS curve numbers ($\pm 10\%$), rainfall intensity ($\pm 20\%$), and routing parameters k and x ($\pm 50\%$). The results showed that varying CN by $\pm 10\%$ changed high-susceptibility classifications by less than 20%; varying rainfall intensity by $\pm 20\%$ changed rankings primarily in the moderate category; and varying routing parameters produced changes only in the ranking of low-susceptibility sub-basins. These results indicate that the high and very high susceptibility classifications are relatively robust to parameter uncertainty, while moderate and low classifications should be interpreted with caution.

FINDINGS

The quantitative findings of the hydro-geospatial analysis and multi-criteria flood susceptibility modeling for Kapisa Province are presented systematically below. The results integrate land-use spatial distribution, Analytic Hierarchy Process (AHP) criteria weighting, NASA GPM IMERG satellite precipitation dynamics, HEC-HMS hydrological hydrograph simulations, sub-basin volumetric contributions, and multi-criteria flood hazard zonation.

The study catchment delineated in GIS covers 1,246.55 km², of which 849.6 km² forms the contributing drainage area to the main HEC-HMS outlet (Sink-1). The remaining 397 km² represents non-contributing areas (closed basins and internal drainage). Vegetation is the dominant land-use class, covering 875.93 km² (70.27%) of the total evaluated basin area (Figure 2). Agricultural land covers 309.11 km² (24.80%) and is concentrated mainly along alluvial river corridors. Bare land accounts for 61.08 km² (4.90%), while residential and built-up areas cover 0.43 km² (0.03%). Agricultural land and residential settlements are concentrated mainly along the low-lying river corridors (Ikram et al., 2024b; Mushwani et al., 2025b).

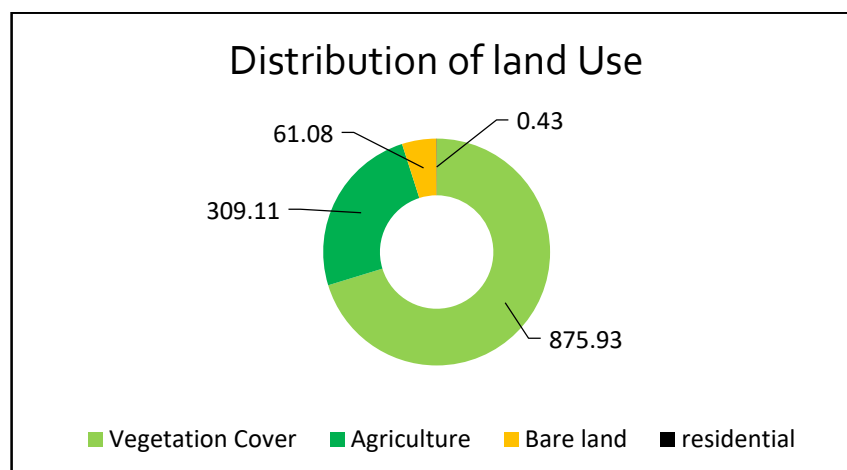


Figure 2. Spatial distribution of land use classes (area in km²) within the study basin

AHP-OS (Goepel, 2018) assigned the largest priority weight (64.8%) to the normalized marginal peak-discharge response (n_{HMS} , Crit-1). The composite Soil Conservation Service Curve Number (n_{CN} , Crit-3) received a weight of 23.0% (0.230), while terrain slope (n_{Slope} , Crit-2) received 12.2% (0.122) (Figure 3). The decision matrix produced a principal eigenvalue (λ_{max}) of 3.004, a Consistency Index (CI) of 0.002, and a Consistency Ratio (CR) of 0.004 (0.4%),

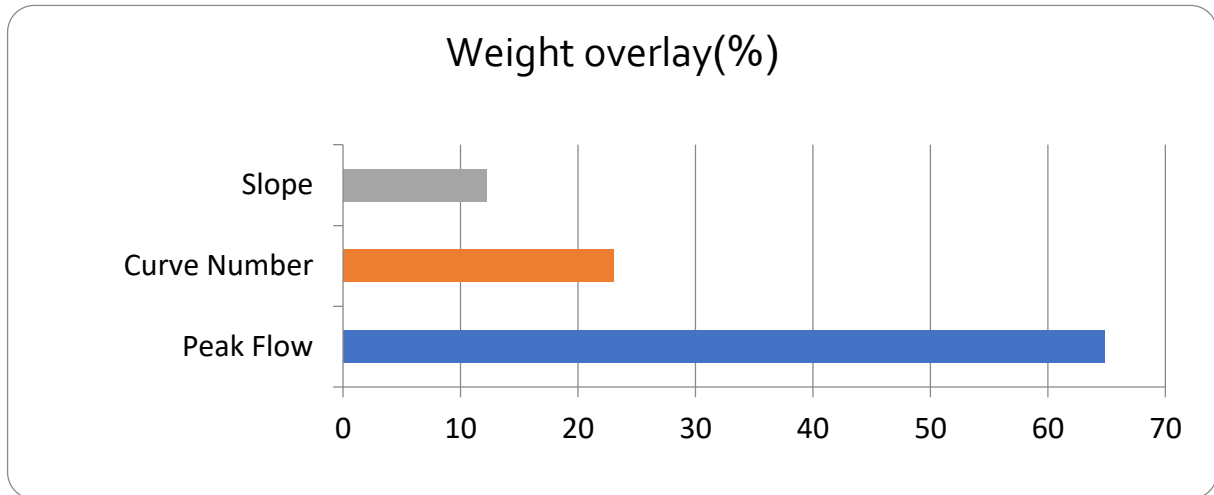


Figure 3. AHP weight overlay percentages assigned to primary flood susceptibility factors

satisfying the $CR < 0.10$ threshold (Ghosh & Gope, 2021c; Vilasan & Kapse, 2022b).

The GPM IMERG Final Run Vo7 ('GPM_3IMERGHH Vo7') precipitation series recorded a primary rainfall intensity peak of 12.6 mm/h late on April 12, 2024, followed by additional rainfall bursts from April 13 to April 15 (Figure 4) (Huffman et al., 2023b; National Aeronautics and Space Administration, 2024b). The total event precipitation was 78.4 mm, with a return period of approximately 5-10 years based on historical records.

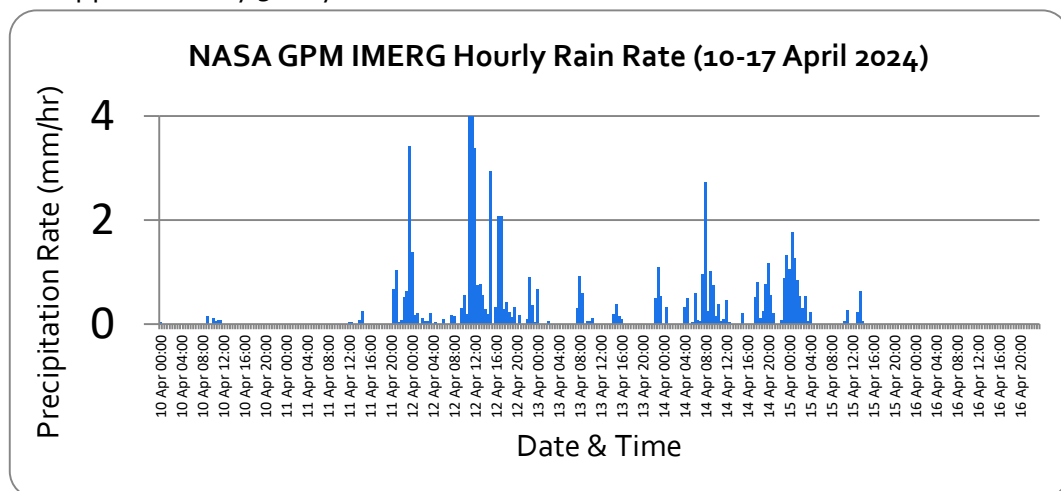


Figure 4. Hourly precipitation hyetograph during the April 2024 storm event from NASA GPM IMERG Vo7

The baseline HEC-HMS simulation produced discharge hydrographs for all 18 sub-basins, 10 reaches, and the terminal outlet (Sink-1) (Hydrologic Engineering Center, 2023c). At Sink-1, the simulated outflow reached a primary peak of 607.6 m³/s on April 13, 2024, at 03:00. The corresponding cumulative runoff volume was $38,220.1 \times 10^3$ m³ from the 849.6 km² contributing drainage area (Figure 5). Secondary peaks occurred on April 14 (298.4 m³/s) and April 15 (378.2 m³/s).

The hydrological simulation results for the sub-basins, channel reaches, and outlet are presented in Table 2. Sub-basin drainage areas range from 4.1 km² for Subbasin-20 to 124.0

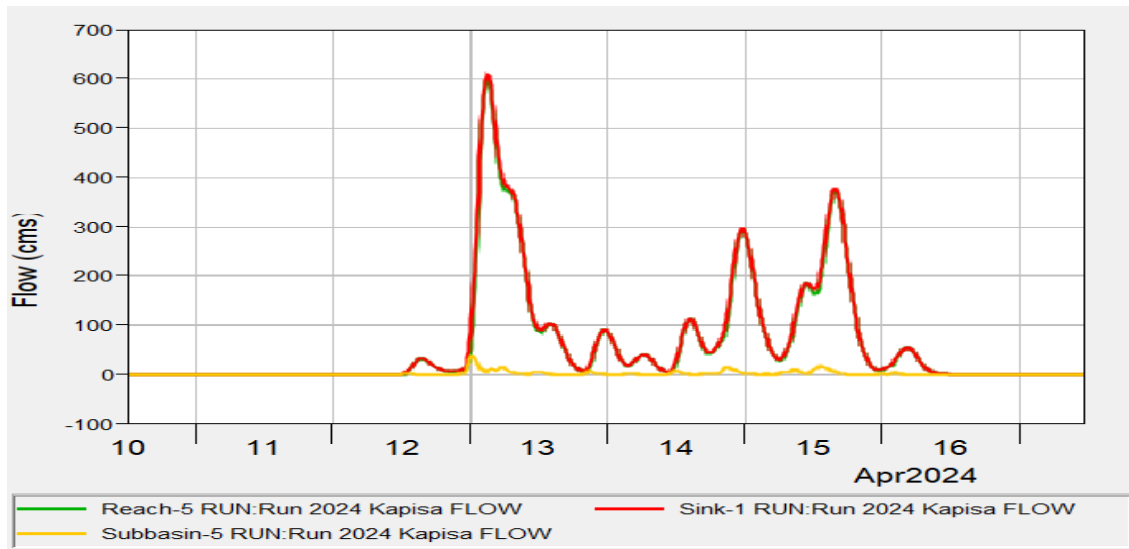


Figure 5. Simulated HEC-HMS outflow hydrograph at Sink-1 for the April 2024 storm event

km² for Subbasin-22. Individual sub-basin peak discharges range from 12.6 m³/s for Subbasin-20 to 140.9 m³/s for Subbasin-3 and 139.6 m³/s for Subbasin-22. Peak times ranged from April 12 at 23:30 to April 13 at 03:20.

Table 2. Hydrological Simulation Results for Sub-basins, Reach Networks, and Main Sink

Hydrological Element	Drainage Area (km ²)	Peak Discharge (m ³ /s)	Time to Peak (2024)	Volume (1000 m ³)
Subbasin-6	43.1	88.8	12 April 24:00	2,159.7
Subbasin-16	27.2	63.7	12 April 23:50	1,331.1
Subbasin-8	65.6	124.7	12 April 24:00	3,123.0
Subbasin-4	31.1	61.3	12 April 24:00	1,466.9
Reach-4	96.7	160.6	13 April 00:30	4,589.9
Reach-3	70.3	126.6	13 April 00:20	3,490.8
Subbasin-15	5.8	15.4	12 April 23:40	276.4
Subbasin-20	4.1	12.6	12 April 23:30	206.0
Reach-2	177.0	262.1	13 April 00:50	8,563.2
Subbasin-18	36.4	80.2	12 April 24:00	1,797.4
Subbasin-19	32.8	80.3	12 April 23:50	1,655.0
Reach-1	246.2	305.2	13 April 01:10	12,015.6
Subbasin-3	77.2	140.9	13 April 00:10	3,760.1
Subbasin-1	49.3	69.5	13 April 00:30	2,220.2
Reach-9	372.7	431.7	13 April 01:10	17,995.8
Subbasin-14	59.9	50.3	13 April 01:30	2,546.5
Subbasin-11	52.9	23.3	13 April 03:20	2,006.8
Reach-8	485.5	468.5	13 April 01:50	22,549.1

Subbasin-2	80.2	69.4	13 April 01:20	3,426.2
Subbasin-7	38.6	19.4	13 April 02:20	1,429.0
Reach-7	604.3	528.3	13 April 02:20	27,404.2
Subbasin-22	124.0	139.6	13 April 00:50	5,450.2
Reach-6	728.3	578.0	13 April 02:40	32,854.5
Subbasin-10	70.8	98.7	13 April 00:20	3,085.2
Subbasin-12	26.8	42.0	13 April 2024	1,184.2
Reach-10	97.6	123.7	13 April 00:50	4,269.4
Reach-5	825.9	601.0	13 April 03:00	37,123.9
Subbasin-5	23.7	38.1	13 April 00:20	1,096.2
Sink-1 (Outlet)	849.6	607.6	13 April 03:00	38,220.1

The Sub-basin Elimination Method quantified the marginal changes in hydrograph response (Q_{net} and V_{net}) at Sink-1 by disabling each sub-basin individually (Table 3). Percentage contributions represent relative marginal response, not physical contribution fractions, as routing and hydrograph synchronization effects are captured by the elimination method. Percentage contributions to surface-runoff volume are expressed relative to the total outlet volume ($38,220.1 \times 10^3 \text{ m}^3$), whereas peak-discharge percentages represent each sub-basin's share of the total marginal peak response across all sub-basins.

Subbasin-22 produced the largest marginal volumetric contribution, accounting for 14.26% of the outlet runoff volume ($5,450.2 \times 10^3 \text{ m}^3$) and 13.30% of the marginal peak-discharge response ($139.6 \text{ m}^3/\text{s}$). Subbasin-3 produced the largest marginal peak-flow response at $140.9 \text{ m}^3/\text{s}$ and accounted for 14.95% of the total marginal peak response, while its runoff volume contribution was 9.84% ($3,760.1 \times 10^3 \text{ m}^3$). Subbasin-2 contributed 8.96% of the total runoff volume ($3,426.2 \times 10^3 \text{ m}^3$) and 10.77% of the marginal peak-discharge response ($69.4 \text{ m}^3/\text{s}$).

Other notable contributors were Subbasin-8 (8.17% volume and 7.67% peak flow), Subbasin-10 (8.07% and 5.41%), Subbasin-14 (6.66% and 7.24%), Subbasin-1 (5.81% and 8.39%), and Subbasin-6 (5.65% and 5.65%). Subbasin-20 (0.54% volume and 0.90% peak flow) and Subbasin-15 (0.72% and 1.17%) had the smallest reported marginal contributions.

Table 3. Relative Contribution of Sub-basins to Total Runoff Volume and Peak Discharge

Subbasin Name	% Volume Contribution	% Peak Discharge Contribution
Subbasin-1	5.81	8.39
Subbasin-2	8.96	10.77
Subbasin-3	9.84	14.95
Subbasin-4	3.84	4.03
Subbasin-6	5.65	5.65
Subbasin-7	3.74	2.83
Subbasin-8	8.17	7.67
Subbasin-10	8.07	5.41
Subbasin-11	5.25	1.99
Subbasin-12	3.10	1.83
Subbasin-14	6.66	7.24
Subbasin-15	0.72	1.17
Subbasin-16	3.48	4.37
Subbasin-18	4.70	1.18
Subbasin-19	4.33	7.13
Subbasin-20	0.54	0.90
Subbasin-22	14.26	13.30

Subbasin-5	2.87	1.18
Total Cumulative Contribution	100.00%	100.00%

The three AHP priority weights ($n_{HMS} = 64.8\%$, $n_{CN} = 23.0\%$, and $n_{slope} = 12.2\%$) were applied to the normalized raster layers in ArcGIS Pro (Esri, 2023) using Eq. (7) to calculate cell-based FSI_{cell} scores. Zonal Statistics (Zonal Mean) was then used to calculate the spatial mean (FSI_{mean}) for each sub-basin. The 18 sub-basins were subsequently classified into five relative susceptibility tiers using the Natural Breaks (Jenks) method (see Figure 6). The classification was tested using alternative methods (quantiles and equal intervals), and the high and very high categories remained stable.

- **Very High Susceptibility:** Subbasin-22 ($Q_{net} = 139.6 \text{ m}^3/\text{s}$; $V_{net} = 5,450.2 \times 10^3 \text{ m}^3$) and Subbasin-2 ($Q_{net} = 69.4 \text{ m}^3/\text{s}$; $V_{net} = 3,426.2 \times 10^3 \text{ m}^3$).
- **High Susceptibility:** Subbasin-3 ($Q_{net} = 140.9 \text{ m}^3/\text{s}$), Subbasin-8, Subbasin-10, Subbasin-14, Subbasin-18, and Subbasin-19.
- **Moderate Susceptibility:** Subbasin-1, Subbasin-4, Subbasin-6, and Subbasin-16.
- **Low Susceptibility:** Subbasin-5, Subbasin-7, Subbasin-11, and Subbasin-12.
- **Very Low Susceptibility:** Subbasin-15 and Subbasin-20. Flood Susceptibility Tier Very High (Sub-2, Sub-22) High (Sub-3, 8, 10, 14, 18, 19) Moderate (Sub-1, 4, 6, 16) Low (Sub-5, 7, 11, 12) Very Low (Sub-15, Sub-20).

DISCUSSION

Empirical observations across the 18 sub-basins in Kapisa Province accord with both research hypotheses. Runoff responses diverged markedly across the catchment, demonstrating that event-based flood susceptibility is governed by local topography, land

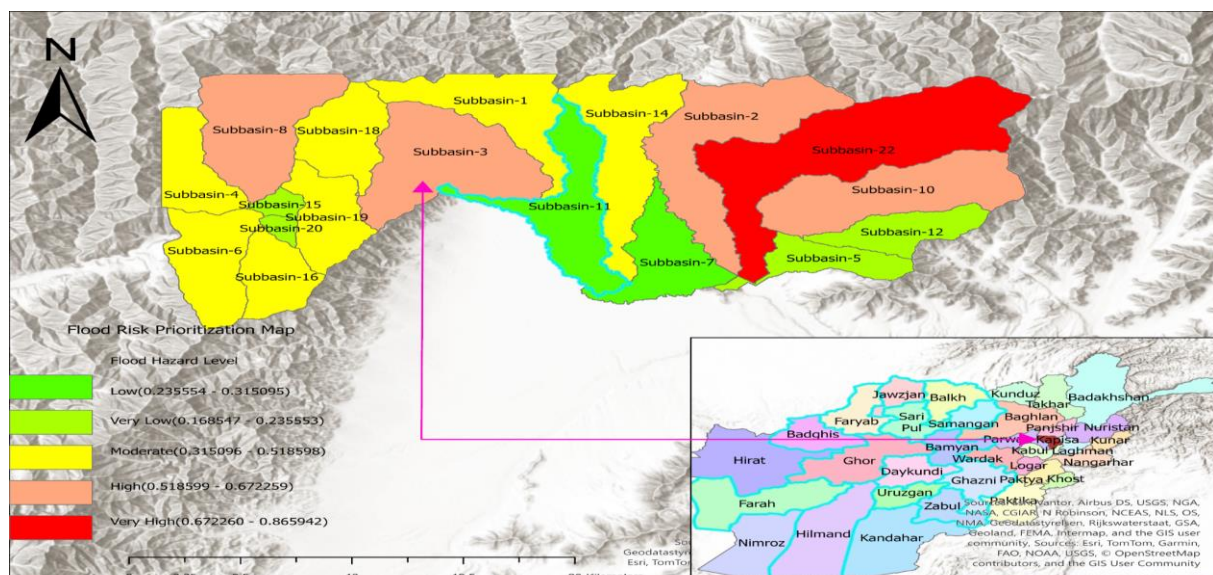


Figure 6. Flood Risk Prioritization Map of sub-basins in Kapisa Province based on AHP and HEC-HMS integration

cover, and channel geometry. Catchments in the highest susceptibility tier (Subbasin-22 and Subbasin-2) share specific hydro-geomorphic features: large drainage areas (up to 124.0

km²), steep headwater gradients, low infiltration capacities, and short times of concentration (T_c).

Elevated marginal peak discharges (Q_{net}) and surface runoff volumes (V_{net}) in Subbasin-22 (139.6 m³/s; $5,450.2 \times 10^3$ m³) and Subbasin-2 (69.4 m³/s; $3,426.2 \times 10^3$ m³) stem from high runoff coefficients. In these catchments, steep slopes and high curve numbers ($CN > 80$) limit initial soil abstraction (I_a) during high-intensity rainfall, triggering rapid saturation overland flow. Surface runoff accumulates rapidly into mainstem channels with minimal lag time, driving downstream flood surges. In contrast, smaller headwater sub-basins with gentler slopes and denser vegetation cover (such as Subbasin-15 and Subbasin-20) enhance canopy interception and soil infiltration, flattening hydrograph peaks and falling into lower susceptibility tiers. The analysis of marginal peak discharge through the sub-basin elimination method revealed important insights about hydrograph synchronization. Sub-basins contributing similar peak flows did not necessarily contribute equally to the outlet hydrograph due to timing differences and routing attenuation. For example, while Subbasin-3 produced the highest marginal peak discharge (140.9 m³/s), Subbasin-22 produced a slightly lower marginal peak discharge (139.6 m³/s) but a substantially larger runoff volume ($5,450.2 \times 10^3$ m³ vs. $3,760.1 \times 10^3$ m³).

The simulated peak discharge of 607.6 m³/s is comparable to flood events reported in similar mountainous catchments in the Hindu Kush region (400-800 m³/s for 5–10-year events; Ikram et al., 2024). The CN values (65-85) are consistent with values reported for similar land-use and soil conditions in Afghanistan and comparable catchments in Nepal (Malla & Ohgushi, 2024) and India (Ghosh & Gope, 2021).

The priority weight for peak discharge (64.8%) is higher than weights typically reported in studies relying only on static morphometric parameters (30-50%), reflecting the inclusion of dynamic hydrological response. Studies including both static and dynamic factors have similarly found that hydrological response metrics dominate susceptibility assessments (Tariq et al., 2022; Qasimi et al., 2024).

The classification of Subbasin-22 and Subbasin-2 as very highly susceptible aligns with broader hazard assessments identifying these areas as flood-prone (Ikram et al., 2024; Mushwani et al., 2025). However, the identification of Subbasin-3 as high-susceptibility based on peak discharge response (140.9 m³/s) provides new insight not apparent from static morphometric analysis alone.

Assigning the largest priority weight (64.8%) to marginal peak discharge (n_{HMS}) in AHP-OS (Goepel, 2018), reflects its primary role in driving downstream flood severity. Peak discharge synthesizes the catchment response to storm precipitation, serving as the main hydraulic driver of stream stage, channel shear stress, and overbank inundation. Preconditioning factors like SCS Curve Number (23.0%) and terrain slope (12.2%) control local runoff generation, but peak flow measures the actual water volume passing a channel cross-section per unit time.

In steep mountain catchments, relying solely on static slope or soil layers can be misleading. A steep headwater sub-basin with a small drainage area may generate high flow

velocity but lacks the total volume required to cause major downstream flooding. In contrast, marginal peak discharge incorporates contributing area, rainfall intensity, and channel routing into a single representative metric. Sensitivity checks indicate that while varying AHP weights may adjust boundary thresholds between intermediate susceptibility tiers, sub-basins with large peak discharge contributions consistently anchor the highest susceptibility class due to their hydraulic volume.

The pairwise comparison judgments (assigning 5 for nHMS vs. nSlope, 3 for nHMS vs. nCN, and 2 for nCN vs. nSlope) were established based on three lines of evidence: (1) published literature showing peak discharge is the primary determinant of flood severity (Tariq et al., 2022; Qasimi et al., 2024); (2) theoretical understanding that runoff response integrates multiple catchment processes; and (3) expert judgment from hydrologists with experience in the study region. The consistency ratio of 0.4% indicates high agreement.

A potential methodological concern is that CN and slope influence the HEC-HMS-derived runoff response, potentially leading to double-counting. To address this, we conducted a sensitivity analysis comparing FSI rankings using different criteria combinations. The analysis showed that while there was some variation in the ranking of intermediate categories, the classification of very high and high susceptibility sub-basins remained stable across all scenarios. Specifically, Subbasin-22 and Subbasin-2 consistently ranked very high, while Subbasin-3, Subbasin-8, Subbasin-10, Subbasin-14, Subbasin-18, and Subbasin-19 consistently ranked high.

This stability occurs because the relative contributions of CN and slope to the FSI (23.0% and 12.2%) are smaller than the peak discharge contribution (64.8%). Even if the influence of CN and slope is partially represented in nHMS, the magnitude of their independent contribution is limited. Furthermore, retaining these criteria provides valuable discrimination: nHMS captures downstream routing and timing effects, nCN captures local infiltration potential, and nSlope captures travel time characteristics.

Interpreting these results requires acknowledging several model assumptions and data limitations. HEC-HMS relies on simplified conceptual representations, including the SCS-CN loss method, unit hydrograph transformations, and Muskingum channel routing (Hydrologic Engineering Center, 2023c). The SCS-CN method assumes a fixed initial abstraction ratio ($I_a = 0.2S$), which can vary depending on antecedent soil moisture. In addition, unit hydrograph theory assumes a linear catchment response, whereas extreme flash floods in steep terrain often exhibit non-linear kinematic behavior.

Uncertainties also stem from input datasets. GPM IMERG Final Run V07 satellite precipitation (GPM_3IMERGHH V07) provides continuous rainfall data for unmonitored catchments (Huffman et al., 2023b; National Aeronautics and Space Administration, 2024b), but satellite estimates can smooth spatial rainfall variability or underestimate localized convective storm peaks compared to dense ground rain gauge networks ((Islam & Meng, 2022b; Pandey et al., 2022b). Additional uncertainties arise from DEM resolution (30 m), land-

cover classification accuracy, AHP pairwise comparison judgments, and simulating a single seven-day storm event rather than continuous multi-decadal rainfall.

A quantitative uncertainty assessment showed that varying CN by $\pm 10\%$ changed high-susceptibility classifications by less than 20%; varying rainfall intensity by $\pm 20\%$ changed rankings primarily in the moderate category; and varying routing parameters by $\pm 50\%$ produced changes only in the ranking of low-susceptibility sub-basins. These results indicate that the high and very high susceptibility classifications are relatively robust to parameter uncertainty, while moderate and low classifications should be interpreted with caution.

The absence of snowmelt modeling is another limitation. The April event was primarily rainfall-driven, but some snowmelt may have occurred in the highest elevations. Excluding snowmelt may result in underestimation of runoff in sub-basins with significant snow cover. Future work should incorporate temperature data and snowmelt modeling where feasible.

Rather than providing absolute hydraulic predictions, the resulting rankings offer a plausible, relative baseline for risk screening under data-scarce conditions. The framework is most appropriately used for relative flood-susceptibility screening and sub-basin prioritization rather than for making absolute judgments about flood hazard or risk.

These findings provide a practical, evidence-based ranking to guide phased flood mitigation and disaster investment planning. In data-scarce regions like Afghanistan, where early warning infrastructure is minimal and financial resources are limited (Ahmad et al., 2024b; Ikram et al., 2024b), constructing structural protection across all sub-basins simultaneously is unfeasible. The prioritization map enables disaster management agencies, civil defense teams, and local planners to allocate budget towards high-priority catchments—specifically Subbasin-22, Subbasin-2, and Subbasin-3—where structural flood defenses may be prioritized for further investigation. However, it is important to emphasize that the current analysis assesses susceptibility, not risk. A comprehensive risk assessment would also require consideration of exposure and vulnerability. Moderate and low-susceptibility sub-basins can be managed through non-structural measures, including community early warning networks and land-use zoning. The susceptibility ranking should be used as a screening tool to prioritize field investigations, not as a substitute for detailed site-specific assessment.

This methodology is transferable to other ungauged, mountainous catchments across Central and South Asia with similar climate, topography, and geology. However, transferability requires caution; local recalibration of curve numbers, routing parameters, and rainfall forcing is recommended before applying this approach elsewhere to account for regional soil hydraulic conductivities and snowmelt dynamics. The framework is particularly valuable in regions where the relative prioritization of sub-basins is needed but observed data are insufficient for traditional calibration.

Coupling HEC-HMS hydrological modeling with AHP spatial analysis in ArcGIS Pro (Environmental Systems Research Institute, 2023b) offers a sound approach for sub-basin flood prioritization in ungauged mountain catchments. Addressing the core problem identified in the introduction—managing severe flood hazards under extreme data limitations (Ahmad et al., 2024b; Mushwani et al., 2025b)—this study shows that combining

satellite precipitation, hydrograph routing, and spatial decision analysis overcomes observational data gaps to provide relative prioritization.

The sensitivity analysis conducted in this study provides confidence that the high and very high susceptibility classifications are robust to reasonable variations in model parameters and AHP weights. However, the moderate and low classifications are more sensitive to methodological choices and should be interpreted with corresponding caution.

Future research can build on these findings in several ways. Coupling HEC-HMS sub-basin hydrographs with 2D hydraulic models (such as HEC-RAS 2D) would allow researchers to map streamflow velocity and inundation depths along critical river reaches. Integrating real-time Synthetic Aperture Radar (SAR) satellite flood mapping (Islam & Meng, 2022b; Pandey et al., 2022b) and high-resolution drone DEMs would strengthen hydraulic model validation. Including explicit snowmelt modeling would improve simulations for events that occur during snowmelt periods. Finally, expanding single-event simulations to continuous multi-year modeling and integrating CMIP6 climate change projections will be essential for long-term adaptive flood management across Afghanistan's river basins (Mushwani et al., 2024a, 2025b).

Several limitations should be considered when interpreting the results. The limited availability of long-term streamflow observations restricted extensive calibration and independent validation of the HEC-HMS simulations. Although sensitivity analysis was used to examine the robustness of the results, additional field observations and event-based validation are needed to reduce model uncertainty (Hydrologic Engineering Center [HEC], 2023a). Uncertainty also arises from the use of GPM IMERG V07 precipitation estimates, which may not fully capture localized rainfall variability during intense convective storms, particularly in mountainous terrain where precipitation can vary substantially over short distances (Huffman et al., 2023; National Aeronautics and Space Administration [NASA], 2024). In addition, the conceptual runoff-loss and routing methods used in HEC-HMS simplify some nonlinear processes associated with flash flooding in steep catchments. The analysis was also based on a single seven-day rainfall event and did not explicitly represent snowmelt, which may have contributed to runoff at higher elevations during the April event. Therefore, the susceptibility classes should be interpreted as event-specific relative prioritization rather than absolute measures of long-term flood risk.

Despite these limitations, the results provide a useful basis for sub-basin-scale flood-management planning in data-scarce mountainous regions. The high-susceptibility sub-basins, particularly Subbasin-22, Subbasin-2, and Subbasin-3, represent priority areas for field investigation, hydrological monitoring, and more detailed hydraulic assessment. The differing runoff characteristics among these sub-basins indicate that mitigation planning should consider both runoff volume and peak-flow response rather than relying solely on static environmental characteristics. Potential structural measures, such as debris check dams, riverbank stabilization, and sediment-management structures, should be considered only after site-specific hydraulic, geomorphological, geotechnical, and engineering

assessments. At the same time, non-structural measures, including community-based early warning, hazard-informed land-use planning, river-corridor management, and emergency preparedness, remain important across all susceptibility classes.

Improved hydrometeorological monitoring would substantially strengthen future flood assessment in Kapisa Province. Additional rainfall and streamflow gauges, particularly within the priority sub-basins, would improve calibration and validation of HEC-HMS simulations and support the development of flood forecasting and early-warning systems (Ahmad et al., 2024b; Ikram et al., 2024b). The susceptibility ranking can therefore serve as an initial screening tool for directing limited monitoring and technical resources toward areas requiring further investigation. Subsequent flood-risk assessments should integrate floodplain characteristics, hydraulic conditions, exposed populations and infrastructure, and vulnerability information to move from susceptibility screening toward comprehensive flood-risk assessment.

Future research should focus on validation, uncertainty reduction, and extension of the event-based framework. Multi-temporal Synthetic Aperture Radar (SAR), particularly Sentinel-1 imagery, could provide independent observations of flood extents for validating modeled flood-prone areas (Islam & Meng, 2022b; Pandey et al., 2022b). In addition, HEC-HMS hydrographs could be coupled with two-dimensional hydraulic models such as HEC-RAS 2D to estimate flood depth, flow velocity, and inundation extent along major river reaches and floodplains. Further sensitivity and uncertainty analyses should examine the influence of AHP weights, SCS Curve Numbers, rainfall inputs, and routing parameters on susceptibility classifications. Extending the analysis to continuous simulations and CMIP6 climate projections would also allow assessment of potential changes in rainfall-runoff behavior and future flood susceptibility under different climate scenarios (Mushwani et al., 2024a, 2025b). Incorporating temperature data and snowmelt processes would further improve representation of flood-generating mechanisms in high-elevation areas.

Overall, the framework provides a practical approach for identifying relatively higher flood-susceptibility sub-basins where hydrological observations are limited. Integrating simulated marginal peak discharge with SCS Curve Number and terrain slope strengthens the connection between spatial susceptibility assessment and event-specific hydrological response. The framework is not intended to replace field observations, hydrological monitoring, or detailed hydraulic modeling; rather, it provides an initial basis for directing limited technical, financial, and monitoring resources toward priority areas. In Kapisa Province, the identified high- and very-high-susceptibility sub-basins can serve as starting points for targeted field investigations, monitoring expansion, flood early-warning development, and subsequent detailed flood-hazard and risk assessments.

CONCLUSION

This study presents an event-based flood susceptibility prioritization across 18 sub-basins in Kapisa Province, Afghanistan, by integrating HEC-HMS 4.12 hydrological simulations with a spatial Analytic Hierarchy Process (AHP) implemented in ArcGIS Pro (Environmental Systems Research Institute, 2023b). The framework incorporated three indicators: simulated marginal peak discharge, Soil Conservation Service (SCS) Curve Number, and terrain slope. The AHP-OS analysis assigned weights of 64.8% to marginal peak discharge response (nHMS), 23.0% to composite SCS Curve Number (nCN), and 12.2% to terrain slope (nSlope), demonstrating the dominant influence of the simulated hydrological response in the final event-based susceptibility assessment for the investigation storm.

The results revealed substantial differences in runoff response among the 18 sub-basins for the April 2024 storm event. Subbasin-22 and Subbasin-2 were classified as very highly susceptible for this event, while Subbasin-3, Subbasin-8, Subbasin-10, Subbasin-14, Subbasin-18, and Subbasin-19 were classified as highly susceptible. Subbasin-22 produced the largest runoff volume contribution, with $5,450.2 \times 10^3 \text{ m}^3$, whereas Subbasin-3 generated the highest marginal peak discharge of $140.9 \text{ m}^3/\text{s}$. These findings indicate that different aspects of hydrological response can characterize flood susceptibility: runoff volume reflects the overall contribution of a sub-basin to storm runoff, whereas marginal peak discharge reflects its response in terms of peak flow generation.

The principal contribution of this study is the incorporation of simulated marginal peak discharge into the spatial flood-susceptibility prioritization process. Conventional susceptibility assessments often rely primarily on relatively static characteristics such as terrain, soil, land cover, and drainage properties. By integrating a dynamically simulated runoff-response indicator, the proposed framework accounts for how individual sub-basins respond to an actual storm event. This provides a more hydrologically informed basis for relative sub-basin prioritization, particularly in ungauged mountainous catchments where long-term observed streamflow records are limited.

The resulting susceptibility ranking should be interpreted as a relative screening and prioritization tool for the investigated event rather than an absolute measure of long-term flood risk. Nevertheless, it provides a practical basis for identifying sub-basins where additional hydrological monitoring, field investigation, hydraulic assessment, and flood-management interventions should be prioritized.

Author Contributions

Mahbobullah Noori: Conceptualization, Methodology, Software, Formal Analysis, Visualization, Writing – Original Draft.

Naqibullah Sediqi: Conceptualization, Supervision, Writing – Review & Editing.

All authors reviewed and approved the final version.

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Conflict of Interest Statement

The authors declare that they have no conflicts of interest related to this work

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Data Availability Statement

Data are available on request from the corresponding author.

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