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Flood Risk Assessment Using GIS and Remote Sensing Technology in Telangana State, India

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***Abstract*:** Recurring flash floods pose a serious hazard in several parts of Telangana State, India, necessitating a comprehensive assessment of flood-prone areas. This study aims to delineate flood hazard risk zones across Telangana using a multi-criteria decision analysis framework integrated with Remote Sensing (RS) and Geographic Information System (GIS) techniques. Key flood influencing parameters; including slope, elevation, aspect, rainfall, drainage density, land use/land cover, soil type, normalized difference vegetation index (NDVI), hillshade, flow accumulation, and topographic wetness index (TWI) were analysed and integrated through a weighted overlay approach. Approximately 40.52% (402 km²) of the area falls within high to very high flood risk categories, while 39.83% (951 km²) was identified as low to very low risk. Specifically, high-risk and very high-risk zones cover 188 km² (18.10%) and 213.7 km² (22.42%) of the region, respectively. The generated flood hazard map provides valuable spatial insights for disaster preparedness, land-use planning, and sustainable flood mitigation strategies, thereby supporting informed decision-making and risk reduction efforts in the state.

***Keywords*:** Flood hazard risk map, Multi-Criteria Assessment, GIS; Remote Sensing, Weighted Overlay Analysis, SRTM.

1. INTRODUCTION

Flooding is one of the most destructive natural hazards worldwide, causing severe socio-economic and environmental consequences. Flood events frequently lead to loss of life, damage to infrastructure, displacement of populations, agricultural losses, and long-term ecosystem degradation. Increasing climate variability, extreme precipitation, rapid urbanization, and land-use changes have further intensified flood frequency and magnitude, particularly in developing regions (Joshi et al., 2025). Consequently, accurate flood susceptibility assessment, defined as the likelihood of an area being affected by flooding, is essential for effective disaster risk reduction, land-use planning, and sustainable development. Remote Sensing (RS) and Geographic Information Systems (GIS) have become indispensable tools for flood susceptibility mapping due to their ability to efficiently process large volumes of spatial and temporal data (Bhukya et al., 2025). Remote sensing provides synoptic and repetitive observations that enable the detection of land cover changes, drainage patterns, and flood extents. GIS enhances flood analysis by enabling the integration, management, and visualization of diverse spatial datasets, including topography, soil characteristics, land use/land cover (LULC), rainfall distribution, and hydrological variables. Through spatial overlay and multi-layer analysis, GIS supports the development of flood susceptibility and hazard maps, providing critical information for decision-making and flood mitigation planning (Refice et al., 2022). The integration of RS and GIS has been widely recognized as an effective approach for assessing flood vulnerability and identifying areas at risk (Tomar et al., 2021; Hagos et al., 2022; Diriba et al., 2024). Various methodological approaches have been employed for flood susceptibility mapping, including statistical models, multi-criteria decision analysis (MCDA), machine learning, and physically based hydrological and hydrodynamic models.

Numerous studies have demonstrated the effectiveness of integrated RS-GIS frameworks combined with probabilistic and MCDA approaches for flood susceptibility assessment (TakeWang et al., 2015). In the Kelantan River Basin of Malaysia, statistical flood susceptibility analysis using RADARSAT imagery provided reliable flood extent information and improved hazard assessment. Similar approaches have been applied in different geographical settings, including the Kosi River Basin in India (Kumar and

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Jha, 2025), the Vamanapuram River Basin (Ajin et al., 2013), and the Lower Awash Sub-basin in Ethiopia (Wondim, 2016). MCDA techniques such as the Analytical Hierarchy Process (AHP) have also been widely adopted to incorporate expert judgment and relative importance of flood-conditioning factors. GIS-based AHP approaches have been successfully used to map flood susceptibility in various regions (Swain et al., 2020). In recent years, machine learning and deep learning techniques including Random Forest (RF), Support Vector Machine (SVM), Naïve Bayes, boosted-tree algorithms, and neural networks have gained increasing attention due to their ability to model complex nonlinear relationships between flood drivers and flood occurrence (Ahmadlou et al., 2023). Physically based hydrological and hydrodynamic models have been applied to simulate flood processes and inundation dynamics, providing detailed insights into flood depth and extent. Coupled hydrological-hydrodynamic frameworks have been successfully implemented in several Indian river basins, including the Damodar, Brahmani Baitarani, and Bengal Basins, to support flood risk mitigation and infrastructure planning (Malik et al., 2020; Ghosh and Kundu, 2023).

The present study was carried out for the Telangana State, India, which frequently experiences flooding that results in significant economic losses and severe impacts on livelihoods. Rapid urbanization, altered drainage systems, and intense monsoonal rainfall have increased flood vulnerability across the region. Despite this, comprehensive flood hazard and risk mapping studies remain limited. Therefore, the present study aims to delineate flood hazard and risk zones in Telangana State using an integrated RS-GIS framework and weighted overlay analysis (Bhukya et al., 2025). The resulting flood hazard maps are expected to support policymakers and planners in developing effective flood mitigation strategies, early warning systems, and sustainable land-use planning initiatives.

2. MATERIALS AND METHODS

This study employs an integrated Remote Sensing (RS) and Geographic Information System (GIS) based approach to develop a flood susceptibility map for Telangana State. The methodology combines satellite-derived datasets with multiple flood-conditioning factors to assess spatial flood susceptibility across the study area. The overall framework was organized into several sequential steps: (1) delineation of the study area, (2) data collection and pre-processing, (3) generation of the land use/land cover (LULC) map, (4) selection and weighting of flood-conditioning factors, (5) weighted overlay analysis, and (6) flood susceptibility mapping. Each step was systematically executed to ensure accurate representation of the physical and hydrological characteristics influencing flood occurrence. The integration of thematic layers through weighted overlay analysis enabled the classification of flood susceptibility zones based on their relative contribution to flood risk.

2.1. Study Area and Data Collection

The present study was conducted for the Telangana State, India, located on the Deccan Plateau in the central part of the eastern Indian Peninsula. The study area lies between latitudes 15°46′ and 19°47′ N and longitudes 77°16′ and 81°43′ E, covering a total geographical area of approximately 114,840 km² and comprising 33 administrative districts. Telangana is predominantly drained by two major river systems, with nearly 79% of its area falling within the Godavari River basin and about 69% within the Krishna River basin. Despite the presence of these major rivers, large parts of the state remain semi-arid in nature. Physio-graphically, Telangana is divided into two agro-ecological regions: The Deccan Plateau and the Eastern Ghats. The state is characterized by a semi-arid climate with predominantly hot and dry conditions. Summer begins in March and peaks in May, during which maximum temperatures often reach up to 42°C. The southwest

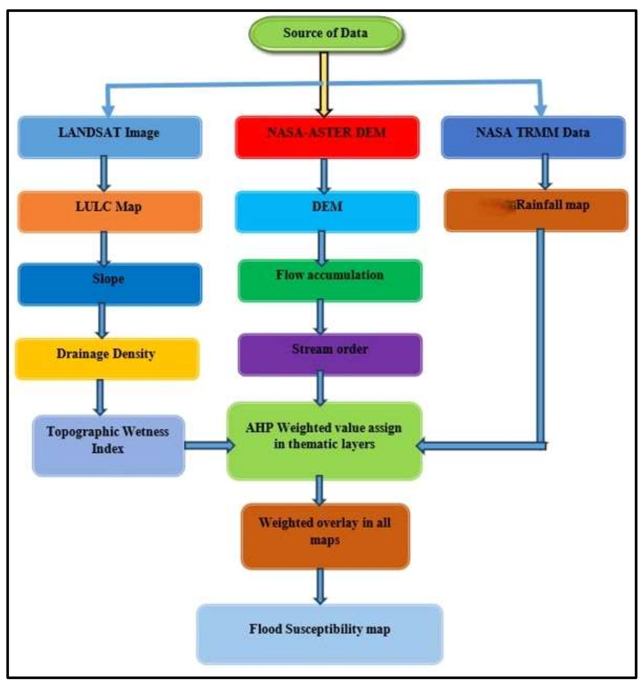

Figure 1. Flow chart of flood susceptibility mapping over the Telangana state

monsoon season extends from June to September and contributes the majority of the annual rainfall. The average annual rainfall varies spatially, ranging from 900-1500 mm in northern Telangana to 700-900 mm in southern Telangana, with nearly 80% of the rainfall occurring during the monsoon period. The winter season, from late November to early February, is generally dry and mild, with average temperatures ranging between 22 and 23°C and relative humidity varying from 25 to 30%.

Flood occurrences in Telangana are primarily driven by prolonged and intense monsoonal rainfall, which overwhelms natural drainage systems and results in surface runoff accumulation. Additional factors influencing flood severity include basin characteristics, drainage density, stream morphology, soil type, rainfall intensity, and anthropogenic obstructions to natural flow paths. In particular, districts such as Khammam are highly vulnerable to monsoon-induced flooding due to their physiographic and hydrological settings. The datasets used in this study, encompassing topographic, hydrological, meteorological, and land use parameters, are summarized in Table 1 and form the basis for flood susceptibility assessment across the state (Bhukya et al., 2025).

2.2. Hillshade

The hillshade layer was generated from the ASTER Digital Elevation Model (DEM) using the Spatial Analyst tools to enhance terrain visualization and support topographic interpretation. The output raster was classified into five categories to represent variations in surface illumination and relief, and subsequently used as an auxiliary layer in flood susceptibility analysis.

2.3. Contour

Contour lines were derived from the ASTER DEM to represent elevation variability across the study area. The generated contour map was used to support the interpretation of terrain configuration and drainage patterns, providing supplementary information for identifying low-lying and flood-prone zones.

2.4. Roughness

Surface roughness was computed from the ASTER DEM to quantify terrain irregularity across Telangana State. The roughness index was classified into multiple classes and incorporated into the analysis to represent spatial variability in surface complexity influencing runoff behaviour.

2.5. Slope

Slope gradients were derived from the ASTER DEM using spatial analysis tool. The slope raster was reclassified into five categories to represent variations in terrain steepness. These classes were incorporated into the flood susceptibility model, considering the influence of slope on runoff velocity and water accumulation (Ahmadlou et al., 2023).

2.6. Elevation

An elevation layer was extracted from the ASTER DEM and classified into five elevation zones using the Spatial Analyst extension. This layer was included in the analysis to account for topographic controls on water movement and flood concentration in low-lying areas (Lappas and Kallioras, 2019; Askar et al., 2022).

2.7. Aspect

The aspect layer was derived from the ASTER DEM at 30 m spatial resolution. Aspect values were classified into directional categories and incorporated into the flood susceptibility analysis to represent terrain orientation effects on surface runoff and drainage behavior (Pham et al., 2021; Askar et al., 2022).

2.8. Flow Accumulation

Flow accumulation was generated from the hydrologically corrected ASTER DEM using standard flow direction and accumulation algorithms. The resulting raster was classified to identify areas of concentrated surface flow, particularly along drainage networks and outlet zones, and

Table 1. Types of data collection and sources

Data type	Sources of data collected	Extracted data
ASTER DEM (Grid) 30 m × 30 m resolution	NASA's official website https://search.earthdata.nasa.gov	Hillshade, Slope, Roughness, Aspect, Elevation, Soil type, Drainage Density, Flow Accumulation and TWI
LULC data (Grid) 10 m× 10 m resolution	ESRI 2020 data, https://livingatlas.arcgis.com/landcover/	Land use/land cover map
Landsat8 Imagery (band5, band4)	USGS official website https://earthexplorer.usgs.gov	NDVI map
Precipitation (TRMM data)	NASA's official website https://giovanni.gsfc.nasa.gov/	Rainfall map

was used as a key indicator of flood-prone locations.

2.9. Drainage Density(D_d)

Drainage density was derived to represent the spatial distribution of stream networks across the study area. Stream order data were extracted from the ASTER Digital Elevation Model (DEM). The drainage density raster was generated using the density tool and subsequently classified into five categories to represent varying degrees of drainage concentration. The computation of drainage density was performed using Eq. (1), and the resulting layer was incorporated into the flood susceptibility analysis.

$Dd = \sum_n^1 L/A$ (1)

Where drainage density is denoted by D_d, the length of waterways is signified by L, and the total area of the basin is signified with symbol A.

2.10. Topographic Wetness Index (TWI)

The Topographic Wetness Index (TWI) was computed to represent spatial variations in terrain-controlled moisture accumulation. TWI was derived from the ASTER Digital Elevation Model (DEM) using flow accumulation and slope rasters. The index was calculated using the standard TWI formulation (Eq. 2) and subsequently classified into multiple categories to distinguish areas of varying wetness conditions. The resulting TWI layer was incorporated into the flood susceptibility analysis to identify zones with a higher potential for surface saturation and flood occurrence (Samanta et al., 2018; Swain et al., 2020).

$TWI = \text{In} AS/\tan(\beta)$ (2)

Where the upstream contributing area is denoted by AS and the gradient of the slope is denoted by β. The final TWI map was divided into five classes showing very low to very high.

2.11. Land Use/Land Cover (LULC)

The Land Use/Land Cover (LULC) layer was prepared to represent spatial variations in surface characteristics influencing runoff behaviour. LULC data for Telangana State was classified into major thematic classes, and the areal extent of each class was quantified. The LULC layer was subsequently incorporated into the flood susceptibility analysis as one of the key conditioning factors.

2.12. Normalized difference Vegetation Index (NDVI)

The NDVI value typically ranges from -1 to +1 (Habibi et al., 2023). Positive NDVI values indicate active vegetation, such as dense forests, while values close to zero represent barren areas. Negative values are associated with water bodies. To create the NDVI map, satellite data were obtained from the Landsat 8 Collection 1, provided by the USGS, and the NDVI values were calculated using the formula (Eq. 3).

The NDVI formula is expressed as:

NDVI = [frac{(NIR - Red)}]/[NIR + Red) (3)

Where the NIR represents near-infrared light and the Red is the visible light. The NDVI map of the study area (Telangana State) was categorized into five sub-categories ranging from −0.26 to 0.62 using the natural break tool (Figure 4). NDVI values typically range from -1 to +1, with higher values indicating healthier and denser vegetation. Here's what different ranges of NDVI values generally signify: Values close to +1 indicate dense, healthy vegetation. Values around 0 indicate little to no vegetation. Negative values are rare in natural environments but can occur in water bodies or highly reflective surfaces like clouds and snow.

2.13. Rainfall

Rainfall plays a crucial role in Telangana, influencing agriculture, water resources, and socio-economic development. Understanding rainfall variability is essential for sustainable water management and climate change adaptation, as rainfall is directly correlated with flood hazards. Rainfall data from the Tropical Rainfall Measuring Mission (TRMM) for the year 2023 were used to generate the rainfall map. The study area was classified into five rainfall sub-categories using the IDW method (Fig. 2m). Owing to its satisfactory performance across different climatic zones of Telangana (Habibi et al. 2023), TRMM data were preferred over other gridded precipitation products. Rainfall weights were assigned based on annual rainfall depth (mm), with higher rainfall regions receiving greater weights due to their stronger influence on flooding. Accordingly, areas with higher rainfall exhibit a greater flood risk. The overall study framework is presented in Fig. 1.

3. RESULTS and DISCUSSION

3.1. Terrain and Morphometric Characteristics

The roughness distribution of Telangana State is presented in Fig. 2a, classified into five categories: very low, low, moderate, high, and very high (Table 2). Low roughness dominates much of the study area, whereas higher roughness values correspond to structurally complex terrains influencing runoff routing and localized water accumulation. Slope values, derived from the DEM, range from 0 to 74.2° and were classified into five subclasses (Figure 2b; Table 2). Most of the study area exhibits gentle slopes, which facilitate water accumulation, while steeper slopes accelerate runoff toward adjacent lowlands. The slope distribution emphasizes terrain-controlled variations in flood risk across the state.

Hillshade analysis (Figure 2c) reveals five classes along with a composite mean hillshade map (Table 2). The classification highlights variations in illumination, slope, and elevation, which indirectly reflect geomorphological controls on surface water flow, erosion, and flood susceptibility. Aspect distribution (Figure 2d) categorizes slope orientation into five classes (Table 2). Spatial variability in slope direction affects runoff pathways, soil moisture retention, and localized hydrological responses, with similar aspect orientations showing clustered flood-prone zones.

Contour maps revealed elevation gradients ranging from 300 to over 800 m above mean sea level (Figure 2e). Low-lying areas coincide with major drainage channels and flood-prone plains, whereas elevated zones act as watershed divides, controlling flow convergence and inundation patterns.

3.2. Vegetation and Land Cover

NDVI classification highlights spatial variability in vegetation density (Figure 2g). Areas with high and very high NDVI correspond to dense forests and croplands, whereas low and very low NDVI values are associated with sparse vegetation and built-up surfaces. The NDVI distribution influences runoff patterns, with denser vegetation promoting infiltration and reducing local flood vulnerability. The 2023 LULC map (Figure 2h, Table 3) indicates that trees cover 62.53% of the area, followed by bare land (18.62%), crops (9.40%), built-up areas (5.56%), flooded vegetation (4.41%), and water bodies (3.70%). Built-up and barren areas exhibit higher flood susceptibility due to lower infiltration and higher surface runoff potential.

Table 2. Details of thematic layers used in the study

Roughness	Class	Score
0-3.9	Very low	5
3.9-10.9	Low	4
10.9-22.6	Moderate	3
22.8-38.7	High	2
38.7-253	Very high	1
Slope	**Class**	**Score**
0-2.3	Very low	5
2.3-61	Low	4
6.1-12.5	Moderate	3
12.5-21.5	High	2
21.5-74.2	Very high	1
Hill shade	**Class**	**Score**
1-53	Very low	5
53.001-114	Low	4
114.01-161	Moderate	3
161.01-204	High	2
204.01-255	Very high	1
Aspect	**Class**	**Score**
0-67.7	Very low	5
67.7-139.7	Low	4
139.7-210.2	Moderate	3
210.2-282.2	High	2
282.2-359.8	Very high	1

3.3. Soil and Hydrological Parameters

Soil distribution includes eight major types: Black Vertisols (BV), Inceptisols (I), Laterite (LC), Lithosols (LP), Natrustalfs (Na), Vertic Clays (Vc), Vertic Paleosols (Vp), and Water-Related Soils (WR) (Fig. 5a). Clay-rich and poorly drained soils correspond to higher flood-prone zones due to reduced infiltration capacity. Flow accumulation values (Figure 2i) are highest along major drainage channels and lowlands, indicating areas prone to surface water convergence and flooding.

Drainage density varies between 21 and 107 km/km² and was classified into five classes (Figure 2j). Lower drainage density is associated with higher flood susceptibility, whereas higher drainage density facilitates efficient runoff, reducing flood risk. The Topographic Wetness Index (TWI) map (Figure 2l) shows regions with persistent moisture accumulation, with higher TWI values corresponding to low-lying and flood-prone zones. The classification into five categories highlights areas of enhanced flood vulnerability across the state.

3.4. Rainfall Distribution

Annual rainfall in Telangana ranges from 615 mm to 1964 mm, with the highest precipitation concentrated in specific regions (Figure 2m; Table 3). Rainfall was classified into five categories: no drought, slight, moderate, severe,

Table 3. Details regarding LULC and rainfall used in the study

LULC class	Percentage (%)	Rainfall (mm/year)	Class
Water	3.70	615-969	Very severe drought
Crops	9.40	969-1140	Severe drought
Trees	62.53	1140-1287	Moderate drought
Built area	5.56	1287-1459	Slight drought
Flooded Vegetation	4.41	1459-1964	No drought
Base ground	18.62		

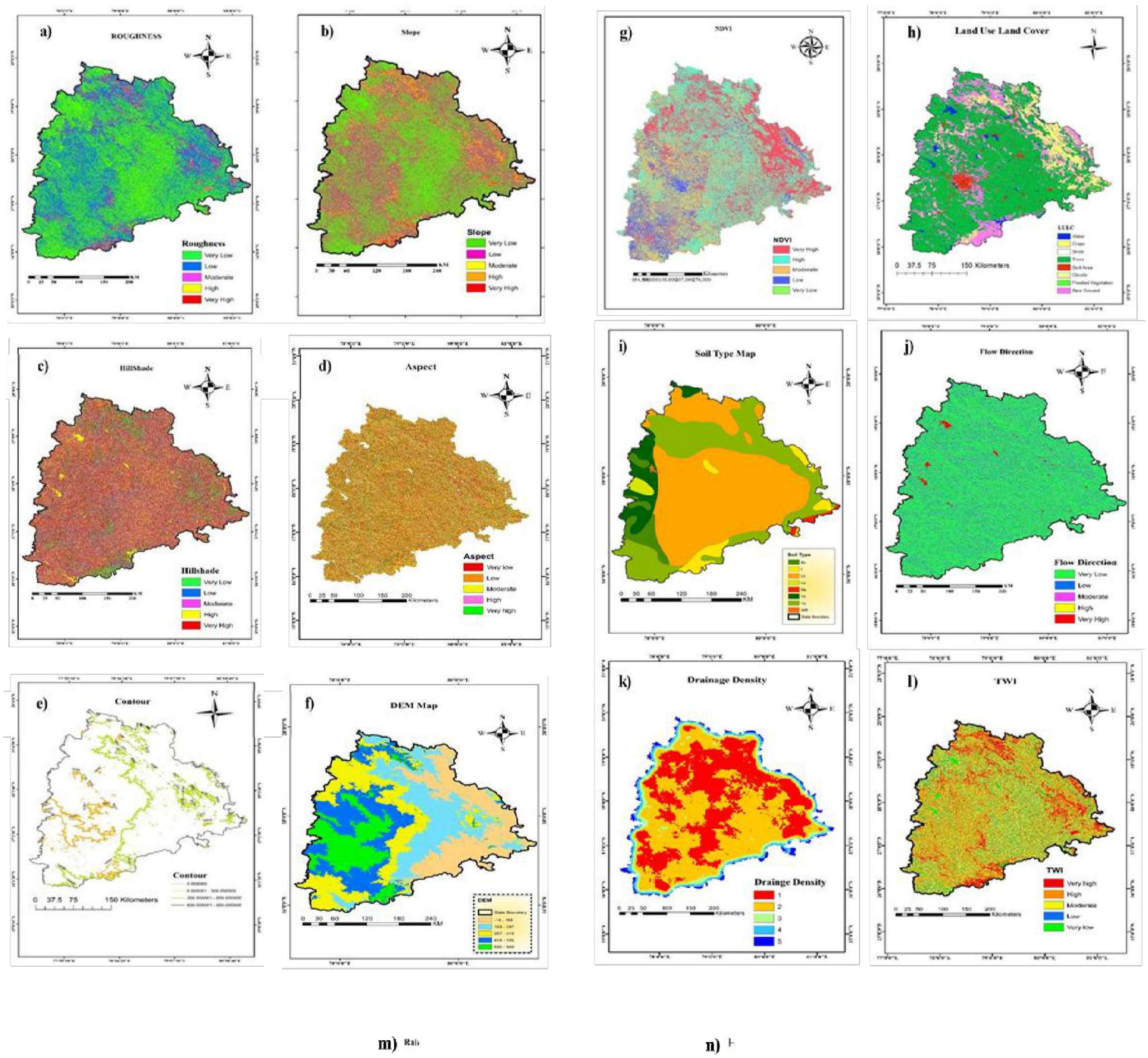

Figure 2. Generated thematic layers a) Roughness b) Slope c) Hillshade d) Aspect e) Contour f) DEM g) NDVI h) LULC i) Soil type j) Flow direction k) Drainage density l) TWI m) Rainfall n) Flood risk map of the study area

and very severe. High rainfall zones correspond to increased flood susceptibility, whereas low rainfall areas exhibit reduced flood risk.

3.5. Influence of Flood-Conditioning Factors

The normalized weights derived as shown in Table 4 showed rainfall as the most influential factor, accounting for 24.56% of the total weight. This is followed by soil type (14.68%) and drainage density (9.56%). Slope (9.52%) also played a significant role, while land use/land cover contributed 7.34%. Hydrological and surface condition indicators such as the Topographic Wetness Index (6.53%), NDVI (5.32%), hill shade (5.24%), and flow direction (5.14%) exhibit moderate influence. Elevation (4.60%) and aspect (4.35%) contributed comparatively less. Overall, these results underscore the integrated influence of topographic, hydrological, and land surface characteristics in shaping flood risk patterns across Telangana.

3.6. Flood Susceptibility Zonation

The integrated flood susceptibility map categorizes Telangana into five classes-very high, high, moderate, low, and very low (Figure 2n; Table 5). Areas identified as having high to very high flood susceptibility represents zones of

Table 4. Normalized weights of different thematic layers used in the study

Factor	Scale	Classes	Weight (%)	Factor	Scale	Classes	Weight (%)
Slope	5	Very low	9.52	LULC	5	Very low	7.34
	4	Low			4	Low	
	3	Moderate			3	Moderate	
	2	High			2	High	
	1	Very high			1	Very high	
Roughness	5	Very low	3.16	Drainage density	5	Very low	9.56
	4	Low			4	Low	
	3	Moderate			3	Moderate	
	2	High			2	High	
	1	Very high			1	Very high	
Elevation	5	Very low	4.60	Flow direction	5	Very low	5.14
	4	Low			4	Low	
	3	Moderate			3	Moderate	
	2	High			2	High	
	1	Very high			1	Very high	
Hillshade	5	Very low	5.24	Soil type	5	Very low	14.68
	4	Low			4	Low	
	3	Moderate			3	Moderate	
	2	High			2	High	
	1	Very high			1	Very high	
Aspect	5	Very low	4.35	TWI	5	Very low	6.53
	4	Low			4	Low	
	3	Moderate			3	Moderate	
	2	High			2	High	
	1	Very high			1	Very high	
Rainfall	5	Very low	24.56	NDVI	5	Very low	5.32
	4	Low			4	Low	
	3	Moderate			3	Moderate	
	2	High			2	High	
	1	Very high			1	Very high	

Table 5. Details of flood risk class of the study area

Flood risk class	Area (km^2)	(%)	Remarks
Very low	535	14.25	Least affected by flooding
Low	416	25.58	Occasional flooding
Moderate	297	19.65	Mostly in south-western, north-central, and eastern areas
High	213.7	22.42	Adjacent to very high flooded regions areas
Very high	188	18.10	Concentrated in western, north-western, and some eastern regions

elevated risk and therefore require priority mitigation and flood management measures. In contrast, regions classified as low to very low susceptibility indicate relatively stable conditions, where the implementation of sustainable land and water management practices can help maintain long-term resilience.

4. CONCLUSION

This study demonstrated the effectiveness of a remote sensing and GIS based approach for identifying flood susceptibility zones in Telangana. Key findings revealed that terrain, hydrology, soil characteristics, vegetation cover, and rainfall are the primary factors influencing flood risk. The integrated analysis highlights areas that are highly vulnerable to flooding and emphasizes the spatial variability of flood susceptibility across the state.

Based on these findings, it is recommended to implement targeted flood mitigation strategies in high-risk areas and adopt sustainable land-use practices in less vulnerable regions to enhance overall resilience. Additionally, incorporating community-based adaptation and early warning systems can further strengthen flood preparedness and management.

Acknowledgments

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Data Availability Statement

All data used in this study are publicly available from the respective data providers as cited in Table 1.

Authors' Contributions

Bhukya Srinivas: Conceptualization, Data curation, Formal analysis, Writing-original draft; Bhupendra Joshi, Ashok Amgoth: Writing-review and editing

Conflict of Interest

Author's declare no conflict of interest.

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