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ORIGINAL ARTICLE

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Assessment of flood susceptibility zones in Kabini catchment of Karnataka, India

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ABSTRACT

Using a geospatial approach, this study analyses the flood susceptibility of the Kabini catchment in Karnataka, encompassing 946 villages in Mysore and Chamarajanagar districts. By integrating Geographic Information Systems (GIS), remote sensing data, and a variety of environmental and hydrological variables, the study aims to create a flood susceptibility map that serves as a tool for informed land-use planning, disaster risk reduction, and mitigation strategies. The methodology involves acquiring and processing both spatial and non-spatial data, followed by the application of Multi-Criteria Decision Making (MCDM) using a weighted product cum geometric mean approach to combine thematic layers such as average rainfall, rainfall-runoff, elevation, slope, topographic indices, drainage characteristics, and vegetation cover. The results delineate varying degrees of flood susceptibility across the catchment, revealing that 587 villages are classified as having low susceptibility, 163 as less susceptible, 116 as moderately susceptible, and 80 as highly susceptible to floods. The comprehensive analysis emphasizes the importance of considering multiple dimensions of flood risk, as these complex interactions between natural and anthropogenic factors contribute to flood vulnerability. This research underscores the importance of a multi-dimensional approach to flood susceptibility mapping, enabling better-informed decision-making and targeted interventions. The findings benefit local stakeholders and serve as a model for other regions facing similar flood risks, contributing to broader disaster risk reduction initiatives.

HIGHLIGHTS

- An extensive assessment in Mysore and Chamarajanagara Districts identified 80 villages as highly susceptible to flooding.
- Key factors such as rainfall intensity, soil moisture, elevation, slope, topography, drainage characteristics, and vegetation cover were comprehensively analyzed to understand each area's flood susceptibility.
- The study underscores the need for a multidimensional approach to flood susceptibility mapping, addressing the complex interplay of factors contributing to flood risks.

1 | INTRODUCTION

Flood susceptibility mapping is essential for understanding and managing flood risks, especially as climate change and urbanization increase the frequency and severity of flooding events. Creating accurate flood maps is crucial for water resource managers. However, several challenges persist. One major issue is obtaining high-quality data, particularly in areas with limited resources or poor data infrastructure. Additionally, the complex nature of floods, influenced by climate change, land use changes, and socio-economic factors, makes it challenging to model flood risk accurately. Flood susceptibility mapping has been extensively researched using a variety of methodologies, demonstrating significant similarities in the approaches and outcomes across different studies. Integrating multiple methods to enhance the accuracy and reliability of flood maps is a common theme.

Several scholars and researchers have done similar work, whereas Akay (2021) employed a combination of statistical methods, fuzzy logic, and multi-criteria decision-making (MCDM) techniques for identifying flood-susceptible zones, while Samanta *et al.* (2018) utilized the geospatial frequency ratio technique to identify flood-prone areas effectively. Mousavi *et al.* (2022) used a comparative analysis between statistical and MCDM methods to assess flood susceptibility in northern Iran, leveraging hydrological and topographical data. Kotecha *et al.* (2023) employed an ensemble GIS-based MCDM-AHP approach to map flash flood susceptibility in the Luni river basin, combining hydrological factors and spatial analysis. Poddar *et al.* (2022) applied a geospatial subjective MCDM model in the Teesta river basin, integrating topographical and rainfall data for flood susceptibility. Mahato *et al.* (2023) assessed various MCDM techniques for flood susceptibility, while Gupta *et al.* (2022) used MCDA-AHP to develop flood risk maps for Assam, integrating hydrological and administrative data. Bera *et al.* (2022) evaluated the effectiveness of machine learning and information theory alongside MCDM in flood mapping under different spatial scales. Vashist *et al.* (2024) applied the AHP method to map flood hazards in the Krishna river basin, while Bora *et al.* (2022) conducted MCDM-based flood susceptibility analysis for the Dibrugarh district, using GIS and hydrological data inputs. Choudhury *et al.* (2022) applied GIS-based AHP modelling for flash flood susceptibility in India, using criteria like slope, land use, and drainage density. Dutta *et al.* (2024) combined MCDM-AHP with multicollinearity and sensitivity analysis for flood risk assessment in the Brahmaputra floodplain, considering hydrological and socio-economic factors. Mitra and Das (2023) and Das and Kamruzzaman (2023) compared GIS-based TOPSIS, VIKOR, and EDAS models for flood susceptibility mapping in the sub-Himalayan foothills, focusing on model performance in different terrains. Pathan *et al.* (2022) implemented AHP and TOPSIS methods to assess dam site suitability in Navsari city, Gujarat. Further studies by (Chakrabortty *et al.,* 2022; Souissi *et al.,* 2020; Das, 2020, Rana *et al.,* 2024; Dutta *et al.,* 2024. Hammami *et al.* (2019) highlight the importance of combining different data sources and analytical approaches to improve flood susceptibility mapping Andaryani *et al.* (2021) integrated hard and soft supervised machine learning techniques, demonstrating the value of combining rigorous data-driven methods with flexible, adaptive algorithms. Similarly, Shafizadeh-Moghadam *et al.,* 2018 employed a novel combination of machine learning and statistical models to enhance flood susceptibility predictions. These integrations reflect a broader trend towards using advanced computational techniques to improve the predictive accuracy of flood maps. Ensemble modelling approaches, which combine multiple algorithms, have shown promise in improving the robustness of flood susceptibility maps. Arabameri *et al.* (2022) used meta-heuristic algorithms. The use of advanced machine learning algorithms, such as those employed by Bui *et al.* (2020), who integrated swarm intelligence algorithms into deep learning neural networks, and Costache *et al.* (2020), who used a neural fuzzy-based machine learning ensemble, further underscores the potential of artificial intelligence in enhancing flood prediction models.

In this context, flood susceptibility mapping studies often share standard methodologies and goals despite specific techniques and geographic focus differences. Integrating statistical methods, machine learning algorithms, GIS, remote sensing data, and MCDA techniques reflects a multi-disciplinary approach to producing accurate and reliable flood susceptibility maps. These maps are crucial for informing land-use planning, disaster risk reduction, and mitigation strategies, ultimately helping to manage and reduce the risks associated with flooding.

The recent advancements in flood susceptibility mapping methodologies include the application of various geospatial and MCDM approaches, particularly focusing on techniques like the Analytical Hierarchy Process (AHP), Weighted Product Model (WPM), and geometric mean methods. Ali *et al.* (2023) conducted a comprehensive study in the Wadi Hanifah Drainage Basin using both AHP and WPM methods, highlighting the significance of these approaches in weighting flood-influencing factors. By employing these models, the authors could assess the contribution of topographical and hydrological factors to flood susceptibility with a high degree of accuracy. Balogun *et al.* (2022) explored a comparative framework, integrating data mining, MCDM, and fuzzy computing techniques for flood susceptibility mapping. Among the approaches, the geometric mean was used as a core methodology for evaluating the influence of multiple criteria, offering a balanced and integrated assessment across spatial domains.

Further, Mudashiru *et al.* (2022) compared two MCDM methods, including the weighted product model, for optimizing flood-influencing factors, particularly emphasizing the efficiency of WPM in integrating multiple criteria for flood hazard evaluation. Their study demonstrated how WPM effectively balances competing factors to generate more reliable flood maps. Nguyen *et al.* (2023) also applied MCDM methods for ranking sub-watersheds in flood hazard mapping, using the geometric mean technique to rank and prioritize areas based on vulnerability. Combining these methods provided a robust framework for spatial flood hazard assessments.

These studies underline the relevance of using techniques like the geometric mean and WPM in geospatial analyses for flood susceptibility mapping. These techniques offer enhanced precision in factor weighting and prioritization, contributing to more accurate flood risk predictions across diverse regions.

2 | MATERIALS AND METHODS

2.1 | Study Area

The Kabini catchment (Fig. 1) geographically extends between 76°3'E to 76°55'E longitude and 11°40'N to 12°20' N latitude, within Karnataka, part of the Cauvery river basin,

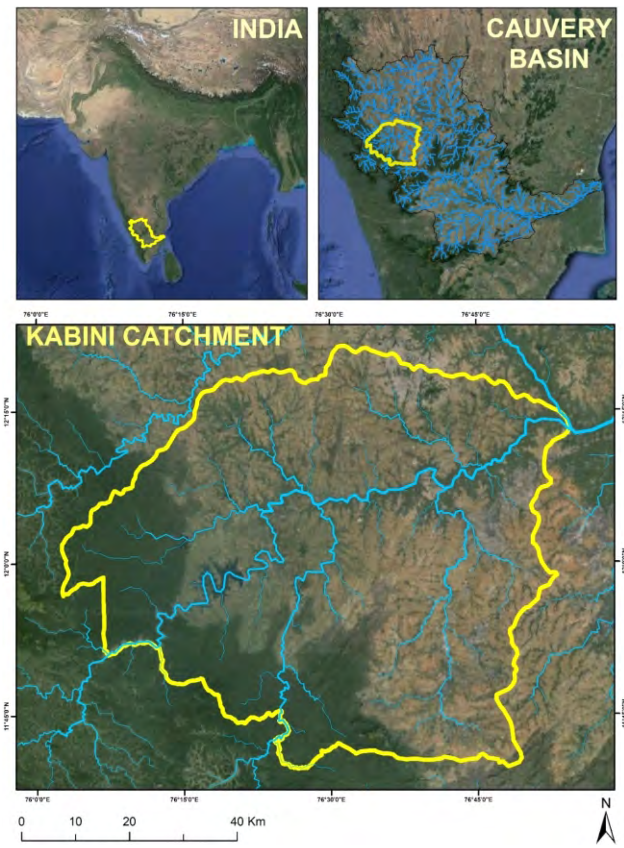
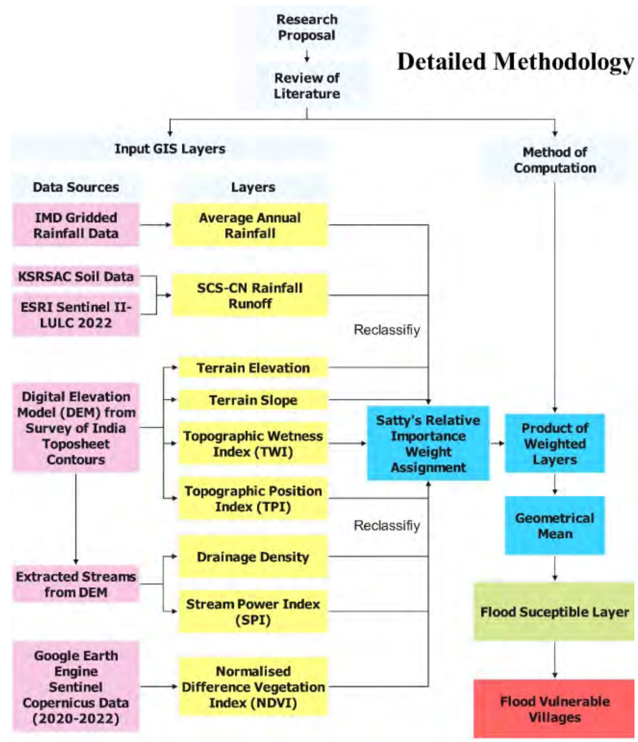


FIGURE 1 Location map of the Kabini catchment



FLOWCHART 1 Methodology of the study

is located in the southern state of Karnataka, India. The study area covers an area of approximately 4908.41 sq km, and its elevation ranges from 650 m to1440 m above the mean sea level. In contrast, the catchment includes parts of Mysore and Chamarajanagar districts within Karnataka. The Kabini river, a major tributary of the Cauvery, originates in the Wayanad hills of Kerala and flows into Karnataka before joining the main Cauvery river. Kabini catchment experiences a tropical climate with a distinct monsoon season, receiving an annual rainfall between 600 mm and 2,000 mm, predominantly during the southwest monsoon. The catchment is primarily agricultural, with crops like paddy, sugarcane, and millet. Forests, including the Bandipur and Nagarhole national parks, cover significant portions and are known for their rich biodiversity and tiger reserves. Kabini reservoir, a vital water source, regulates irrigation and drinking water supply. The river system is also critical for downstream water management in the Cauvery basin. The Kabini catchment has a history of recurrent flooding, primarily driven by the southwest monsoon. Floods in this region are influenced by heavy rainfall, the topography of the Western ghats, and the riverine systems that drain into the Kabini river. Flood studies are critical for regions like the Kabini catchment, prone to recurrent flooding. Understanding the causes, patterns, and impacts of floods is pivotal in planning, development, and disaster management.

The methodology employed (Flowchart 1) for flood susceptibility mapping in the Kabini basin integrates geographic information systems (GIS) and remote sensing (RS) techniques with MCDM approaches. The process involves several key steps:

Spatial and non-spatial data were acquired from various sources (Table 1). Selection of flood influencing factors was identified through a review of literature such as average annual rainfall, rainfall-runoff, elevation, slope, topographic wetness index (TWI), topographic position index (TPI), drainage density (DD), stream power index (STPI) and normalised difference vegetation index (NDVI). Each factor was standardized and assigned a weight based on its influence on flooding through MCDM approach based on Saaty's AHP's relative importance weight assignment techniques was employed for assigning relative weight for each raster data, and weighted product model (WPD) was employed to integrate various flood influencing factors. Using suitable threshold values, the flood susceptibility index was classified into different susceptibility zones (e.g., very low, low, moderate, high, and very high). The final flood susceptibility map was validated using historical flood data and statistical measures to assess its accuracy and reliability.

Rainfall runoff is estimated using the soil conservation service (SCS) curve number (CN) method, a hydrological

TABLE 1 Data Source and Method of Processing

S.No.	Layer Name	Data Sources	Techniques used to prepare raster layer
1	Average Annual Rainfall	IMD Gridded File (1990-2023)	Spatial Interpolation Inverse Distance Weighted (IDW) through ArcGIS Software
2	Soil Data	KSRSAC, Bangalore	
3	Land Use Land Cover (LULC)	ESRI Sentinel II, 2022	
4	SCS-CN Numbers	USDA	
5	Contours	Survey of India Toposheet	Digitisation through ArcGIS Software
6	Terrain Elevation, Digital Elevation Model (DEM)	Contours as per S.N.5	Interpolation through ArcGIS Software
7	Terrain Slope	DEM as per S.N.6	Slope Estimation through ArcGIS Software
8	Topographic Wetness Index https://saga-gis.sourceforge.io/saga_tool_doc/2.3.0/ta_hydrology_20.html	DEM as per S.N.6	Through SAGA GIS Software Formula: TWI = ln(flow_accumulation / tan(slope))
9	Topographic Position Index https://saga-gis.sourceforge.io/ saga_tool _doc/2.2.0/ ta_morphometry_18.html	DEM as per S.N.6	TPI = z0 - z¯, where z0 is the elevation at the central point, and z¯ is the average elevation around it within a predetermined radius. A positive value of TPI indicates Ridges or hills, and a Positive value of TPI indicates Valleys or pits.
10	Drainage Density https://pro.arcgis.com/en/pro-app/latest/tool-reference/spatial-analyst/line-density.htm	Streams Extracted from DEM as per S.N.6	Kernel Density Estimation (KDE) through ArcGIS Software
11	Stream Power Index https://saga-gis.sourceforge.io/ saga_tool_doc/2.2.5/ ta_hydrology_21.html	Streams as per S.N.6	Through SAGA GIS Software SPIi = ln(DAi * tan (Gi)) where SPI is the stream power index at grid cell i, DA is the upstream drainage area (flow accumulation at grid cell i multiplied by grid cell area), and G is the slope at a grid cell i in radians.
12	Normalised Difference Vegetation Index (NDVI)	Sentinel Copernicus	NDVI = (NIR - RED) / (NIR + RED) NIR = Near Infrared Band Image RED = Red Band Image
13	Flood Susceptibility Map	Weighted Product Geometric Mean	$\left(\prod_{i=1}^{n} x_i\right)^{\frac{1}{n}}$ (Product of all nine weighted layers)^1/n, where n= 9 according to the present study.

tool developed by the US Department of Agriculture (USDA)'s Natural Resources Conservation Service (NRCS). The CN method assigns values (0-100) to different land uses (Fig. 4) and soil types (Fig. 3), indicating runoff potential. Lower CN values represent higher infiltration and lower runoff, while higher CN values indicate the opposite. Soils are classified into four groups by the NRCS: Group A (high infiltration, e.g., sands), Group B (moderate infiltration, e.g., loams), Group C (slow infiltration, e.g., clays), and Group D (very slow infiltration, e.g., high shrink-swell clays, rock outcrops). Based on the soils of the Kabini basin (Fig. 3) have grouped into SCS hydro groups of (A, B, C, and D), and Land use land cover (Fig. 4) correlated with the (Fig. 3) and generated the SCS-CN value (Fig. 5) for the Kabini basin.

TWI is a valuable tool in evaluating the potential susceptibility of an area to flooding. This index, developed by MJ Kirkby in 1975, integrates two key topographic characteristics: slope and upslope contributing area. TWI with higher values indicates areas with greater potential for water accumulation and, consequently, higher susceptibility to flooding. This is because a larger upslope contributing area (A) and a lower slope (β) lead to slower water flow and increased likelihood of ponding. Conversely, Lower TWI values represent areas with better drainage capabilities due to steeper slopes and smaller contributing areas. These areas are generally considered less susceptible to flooding.

The topographic position index (TPI) is another valuable tool for assessing flood susceptibility. It enables us to characterize the landscape's morphological features by analysing and categorizing slope gradients. This index serves as a means of delineating slope positions and identifying various geomorphological types.

Stream density is crucial in influencing flooding events, especially in areas with high stream density. These regions often face limited channel capacity, leading to difficulties managing increased water flow during heavy rainfall. In mountainous areas like the Kabini river basin, numerous tributaries from hills and foothills feed into the main river, such as the Nugu, Hullahalla, Suvarnavathi, and

Kapila rivers. Human interventions like dams, such as the Kabini dam near Beechanahalli village, alter drainage patterns by regulating downstream water flow.

The stream power index (SPI), developed by Lane in 1955, assesses an area's susceptibility to flooding based on the erosive power of flowing water, influenced by factors like catchment area and slope gradient.

Normalized difference vegetation index (NDVI) is a widely used remote sensing metric that quantifies vegetation health and density by measuring the difference between near-infrared and visible red light reflected by vegetation.

Weighted geometric mean (WGM) is selectively adopted by Xu (2000); Yousefi *et al.* (2015); Tennakoon (2023); Krejčí, *et al.* (2018); Shekar, *et al.* (2023); Melese, *et al.* (2022) and the same applied to the current study for compiling the flood hazard maps.

3 | RESULTS AND DISCUSSION

3.1 | Average Annual Rainfall

Rainfall significantly affects flood susceptibility, as higher rainfall leads to more surface water accumulation, exceeding soil and drainage system capacities. The Kabini catchment, with a tropical sub-humid climate, receives 800-1200 mm (IMD, Pune) of rainfall annually (Fig. 2), predominantly during the southwest monsoon (June-Sept) and to a lesser extent from the northeast monsoon (Oct-Dec). Despite moderate rainfall, the region experiences high evapotranspiration (1200-1550 mm/yr), creating a semi-arid condition. The climate is characterized by moderate monsoon-influenced rainfall, high evapotranspiration, and variable rainfall patterns.

3.2 | Rainfall Runoff

The breakdown of soil subgroups and hydro groups along with their respective areas in (km^2) of the Kabini basin showed that the soil subgroups range from *Typic Haplustalfs* to *Lithic Rhodustalfs*, each belonging to a hydro group categorized as A, B, C, or D. Among the soil subgroups, *Typic Haplustalfs* occupies the largest area with 631.54 km^2, followed closely by *Aquic Haplustepts* at 606.22 km^2 and *Typic Haplustepts* at 573.60 km^2. *Pachic Argiustolls* and *Typic Rhodustalfs* also cover substantial areas, with 490.68 km^2 and 486.49 km^2, respectively. Notably, *Lithic Ustorthents,* Waterbodies, and Impervious Surfaces represent smaller areas, with 169.64 km^2, 169.12 km^2, and 145.21 km^2, respectively. These classifications provide valuable insights into the distribution of soil subgroups and hydro groups within the studied area, facilitating informed land management and environmental planning decisions based on soil characteristics and hydrological considerations.

3.3 | Elevation and Slope

The Kabini basin encompasses portions of the Western ghats, a mountain range known for its rugged terrain and

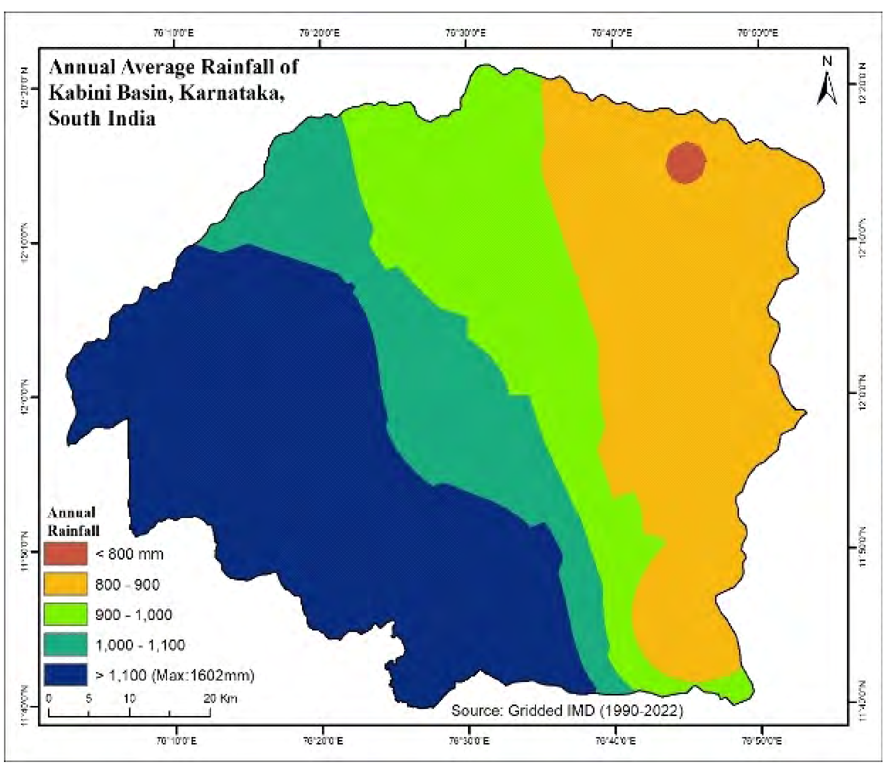


FIGURE 2 Annual Average Rainfall

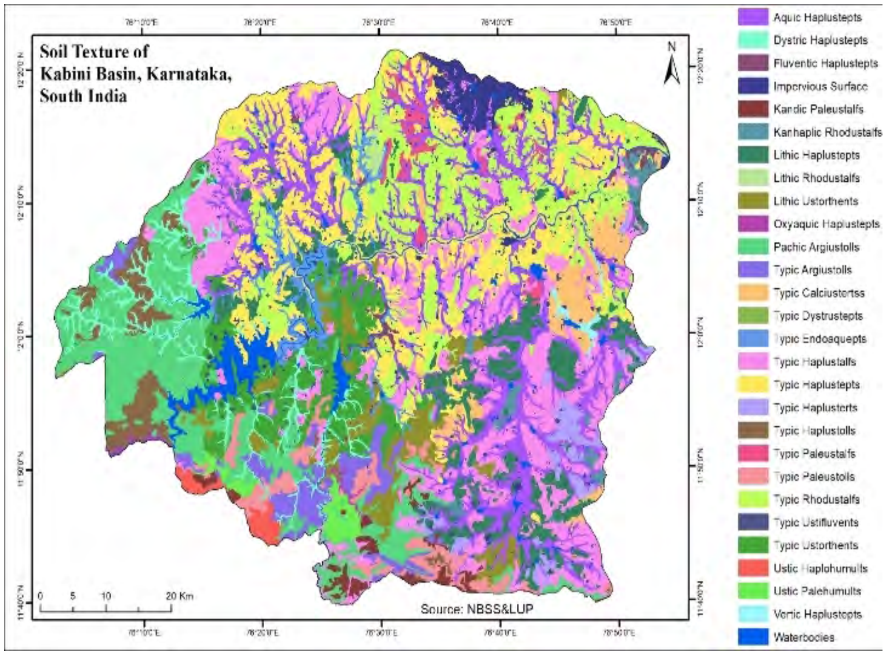


FIGURE 3 Soil Texture

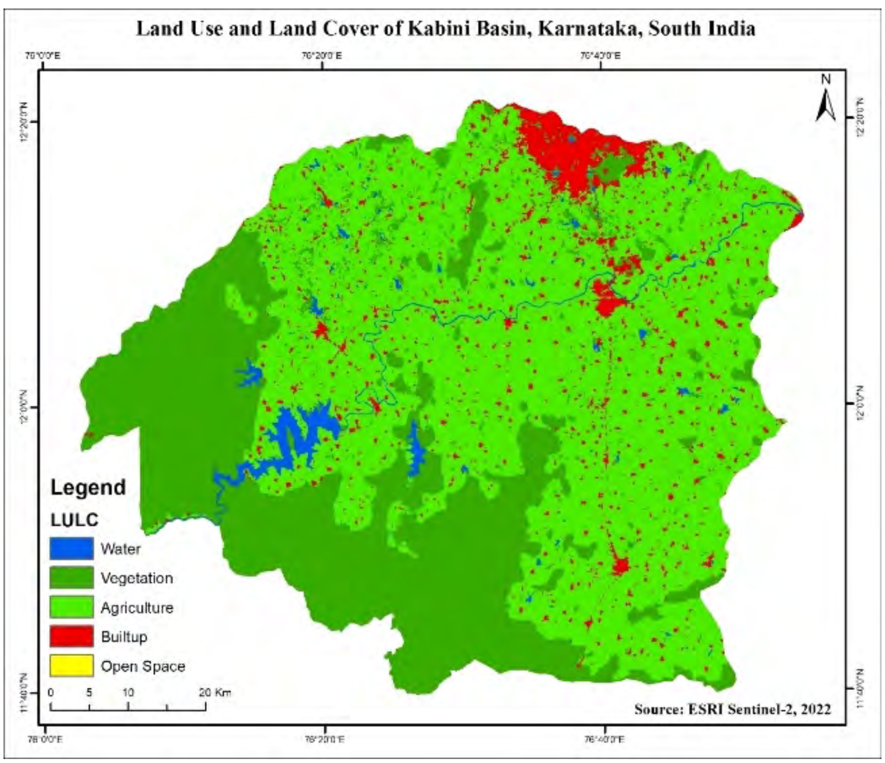


FIGURE 4 Land use

high elevation. These highland areas contribute to the basin's headwaters, with numerous streams and rivers originating from the slopes and foothills. Understanding the influence of topography, particularly elevation and slope, is crucial in assessing flood susceptibility. These factors play a critical role in determining the flow path, velocity, and accumulation of floodwaters, ultimately impacting the risk of inundation in different morphologies of the topography. Landforms with base-level elevations are generally more susceptible to flooding due to their proximity to water sources like rivers, lakes, and coastlines. These areas are the first to experience inundation during flood events as

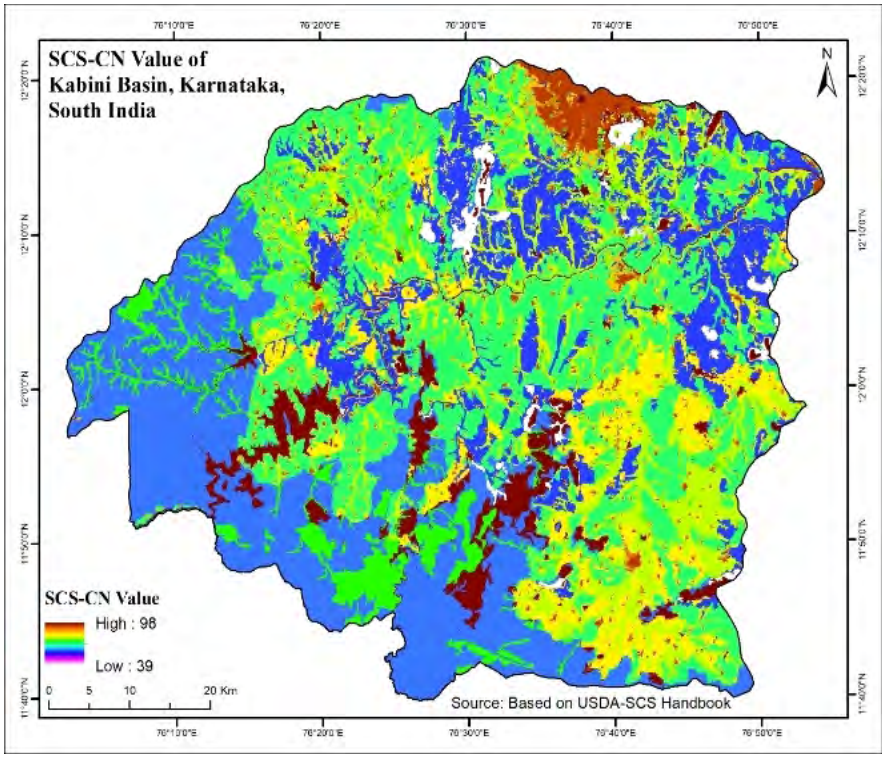


FIGURE 5 SCS-Soil CN Curve

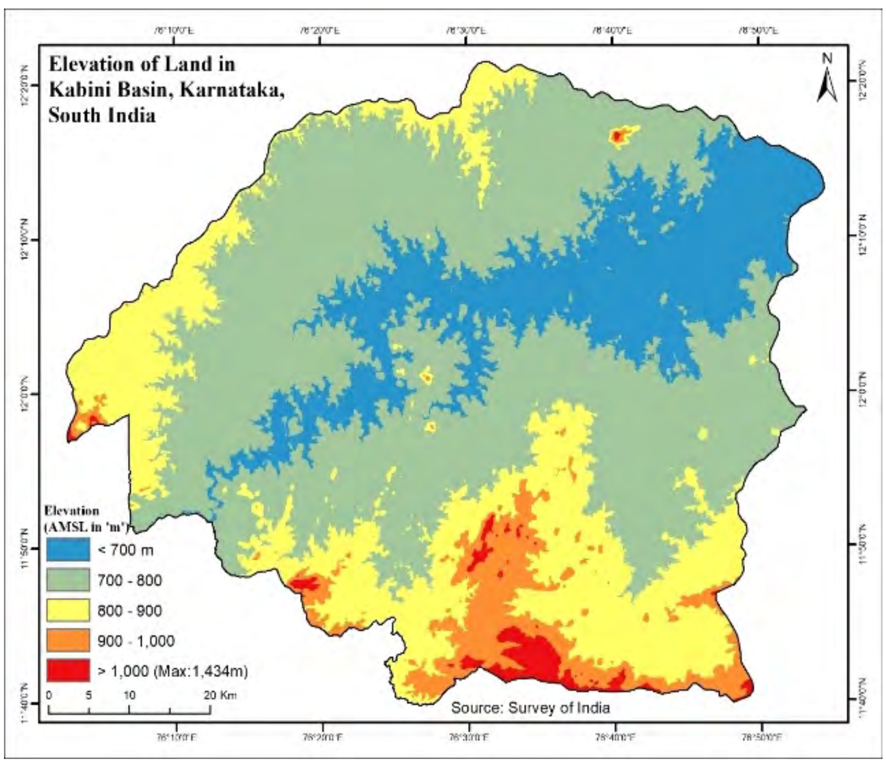


FIGURE 6 Digital Elevation Model

overflowing water accumulates and has nowhere else to go. Both elevation (Fig. 6) and slope (Fig. 7) are critical factors shaping flood susceptibility. While low-lying areas and flatter slopes generally exhibit higher susceptibility, the interplay with other topographical and hydrological elements necessitates a holistic approach to flood risk evaluation.

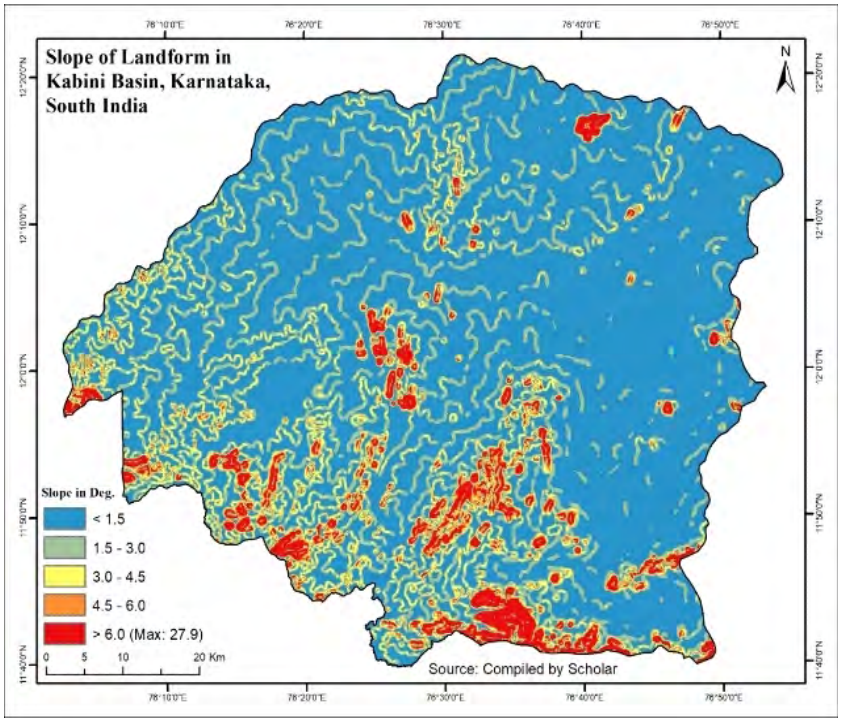


FIGURE 7 Slope

3.4 | Topographic Wetness Index (TWI) & Topographic Position Index (TPI)

TWI (Fig. 8) is a crucial layer in mapping flood susceptibility and provides valuable insights into potential flood risk based on topographic characteristics. The TPI generates a map of continuous values (Fig. 9). Defining thresholds to classify landforms and valuable insights into flood susceptibility by analysing relative elevation compared to the surrounding terrain is beneficial for geomorphological analysis.

3.5 | Drainage Density and Stream Power Index

Stream density, or drainage density (Fig. 10), refers to the concentration of streams or rivers within a specific geographic area. Higher SPI values indicate (Fig. 11) greater erosive power and potential flood risk due to increased water velocity and channel erosion, while lower SPI values suggest reduced flood susceptibility.

3.6 | Normalised Difference Vegetation Index (NDVI)

NDVI can provide valuable insights into flood impacts on vegetation and ecosystem health. During flooding events, NDVI values often decrease due to inundation and stress on vegetation caused by excessive water levels. Monitoring changes in NDVI before, during, and after floods can help assess flood extent, vegetation damage, and recovery rates. NDVI (Fig. 12). values range from -1 to 1, with higher values indicating healthier and denser vegetation cover. In the context of flooding, By integrating NDVI data with flood mapping and hydrological models, stakeholders can better understand the ecological consequences of flooding, plan effective mitigation measures, and support ecosystem restoration efforts in affected areas.

3.7 | Flood Susceptibility

In the context of flood susceptibility mapping in GIS, the "Weighted Geometric Mean" could combine multiple flood hazard layers into a single composite layer that reflects the relative importance of each layer. Weight assignment follows Satty's relative importance scale to the layers based on their reliability, accuracy, or importance in flood mapping. Weighted product is a mathematical method used in decision- making and multi-criteria analysis to combine multiple criteria or factors into a single composite score. Each criterion is assigned a weight that reflects its relative importance or priority in this method. The weighted product of each criterion is calculated by multiplying its value by its corresponding weight. Then, the individual weighted products are multiplied together to obtain the overall composite score. The weighted product method is beneficial when dealing with diverse criteria with varying importance levels. By assigning weights to each criterion, decision-makers can ensure that factors considered more significant have a greater influence on the final result. This allows for a systematic and transparent approach to decision-making, where the relative importance of different factors is explicitly considered.

For each cell or pixel in the GIS raster layers, compute the weighted product of the values in the corresponding cells across all layers. This involves raising each value to the

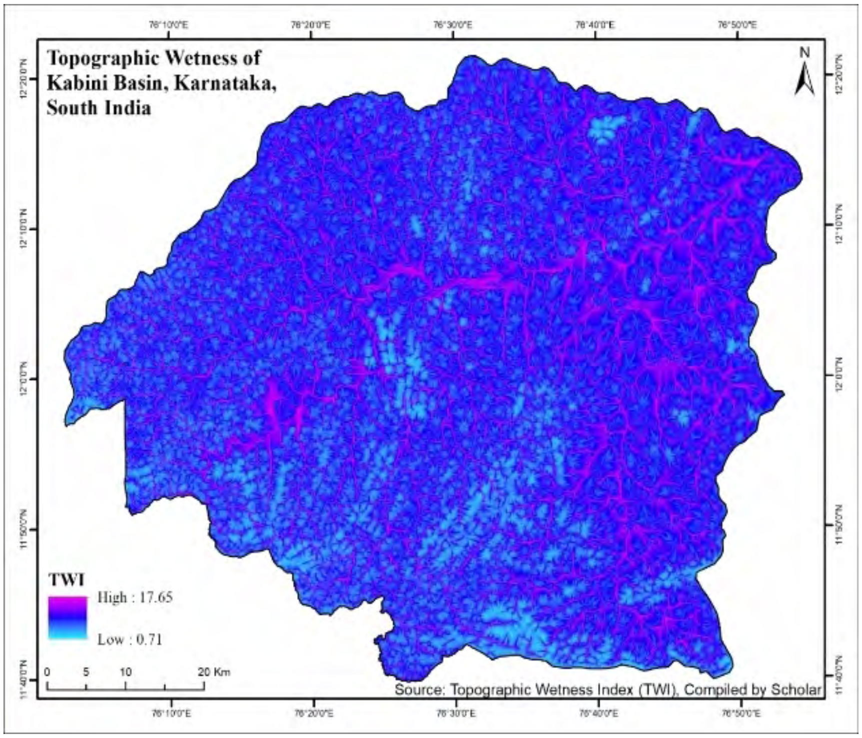


FIGURE 8 Topographic Wetness

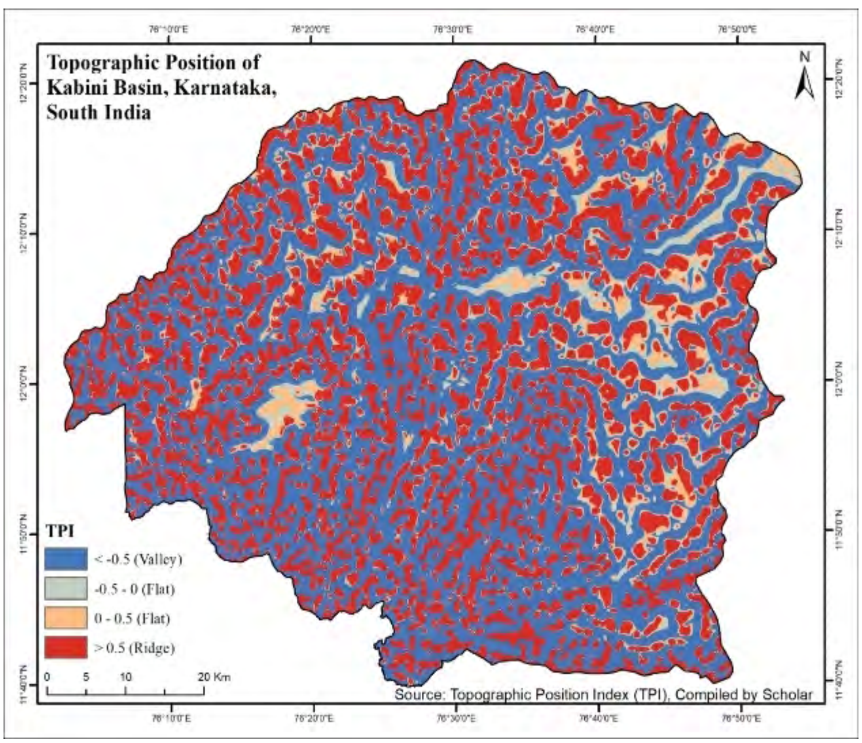


FIGURE 9 Topographic Position Index

power of its assigned weight. Then, calculate the geometric mean of these weighted products across all layers. This is achieved by taking the nth root of the product, where n is the total number of layers.

By incorporating the weighted geometric mean approach, the resulting flood susceptible map (Fig. 13, 14) can better capture the complexities of flood risk by integrating multiple data sources while accounting for their varying

TABLE 2 Susceptible Layers and Weights

1	Parameter	Range	Susceptibility	Ranking	Weights
	Rainfall Intensity in mm	< 800 mm	Very Low	1/4	0.25
		800 - 900	Low	1/4	0.25
		900 - 1000	Moderate	1/3	0.33
		1000 - 1100	High	½	0.5
		> 1100 mm	Very High	1	1
2	SCS-CN Rainfall Runoff	0-100	Low to High	Min-Max Scaled to [0-1]	
3	Elevation in m	< 700 m	Very High	1	1
		700 - 800	High	½	0.5
		800 - 900	Moderate	1/3	0.33
		900 - 1000	Low	1/4	0.25
		> 1000 mm	Very Low	1/4	0.25
4	Slope in Degrees	< 1.5 (Flat)	Very High	1	1
		1.5-3.0	High	1/2	0.5
		3.0-4.5	Moderate	1/3	0.33
		4.5-6.0	Low	1/4	0.25
		> 6.0 (Steep)	Very Low	1/4	0.25
5	Topographic Wetness Index	< 3.0 (Dry)	Low	1/3	0.33
		3.0 - 6.0	Moderate	1/2	0.5
		> 6.0 (Wet)	High	1	1
6	Topographic Position Index	< -0.5 (Valley)	High	1	1
		-0.5 to 0.5 (Flat)	Moderate	1/2	0.5
		> 0.5 (Ridge)	Low	1/3	0.33
7	Drainage Density	0-4	Low to High	Min-Max Scaler to [0-1]	
8	Stream Power Index	< 0	Low	½	0.5
		> 0	High	1	1
9	NDVI	-1 to 1	High to Low	Min-Max Scaled to [1-0]	

TABLE 3 Flood Susceptible Area in Kabini Catchment of Karnataka

S.No.	Flood Susceptibility Index [0-1], Low to High	Area km^2
1	0.00 - 0.50 (Low)	3258.29
2	0.50 - 0.75 (Medium)	1354.80
3	0.75 - 1.00 (High)	289.99

levels of importance or reliability. Flood susceptibility maps varied across the spatial scale and quantified that out of 4899 km^2 Kabini catchment, 289.99 km^2 have the higher susceptibility, 1354.80 km^2 has moderate susceptibility, and 3258.29 km^2 has low susceptibility.

3.8 | Villages Prone to Flood Risk at Kabini Basin

In a comprehensive assessment (Fig. 15) covering 946 villages from the districts of Mysore and Chamarajanagara, varying degrees of flood susceptibility were observed (Fig. 14). Among these villages, 587 were identified as having no significant susceptibility to flooding, suggesting a relatively lower risk level. In contrast, 163 villages were categorized as experiencing less susceptibility to floods, indicating a potential but less imminent threat. Furthermore, 116 villages were classified under the medium susceptibility category, suggesting a moderate risk of flood events. Notably, 80 villages were designated as high susceptibility areas, indicating a considerable vulnerability to flooding, requiring urgent attention and robust mitigation measures to minimize potential damage and ensure the safety of residents. These findings underscored the importance of proactive measures. They targeted interventions to address flood risks in high-susceptibility areas while implementing preventive strategies in regions with lower susceptibility to enhance overall resilience to flooding events.

3.9 | Validation of Result

To validate the flood risk assessment of the Kabini basin, this study references a detailed flood impact analysis of Nanjangud by Manjunatha and Basavarajappa (2022), where flash flooding from the Kabini (Kapila) river led to widespread inundation, severely affecting critical infrastructure, agricultural areas, and local communities. In the Nanjangud study conducted by Manjunatha and Basavarajappa (2022), significant inundation occurred in key locations, including the Srikanteshwara Temple, 16 Pillar Pavilion, Mallanamoole Mutt, Sutturu Mutt, Ayyappa Temple, Parashuram Temple, Chamundeshwari Temple, Chikkamma Chikka Devi Temple, and several streets near the main temple area. Additionally, crucial infrastructure like the Mysuru-Nanjangud National Highway (NH-766), Nanjangud Bridge, Hommaragalli Bridge, Madapura Bridge, and roads leading to Hosakote and Sutturu were submerged, disrupting connectivity and highlighting vulnerabilities in these flood-prone zones.

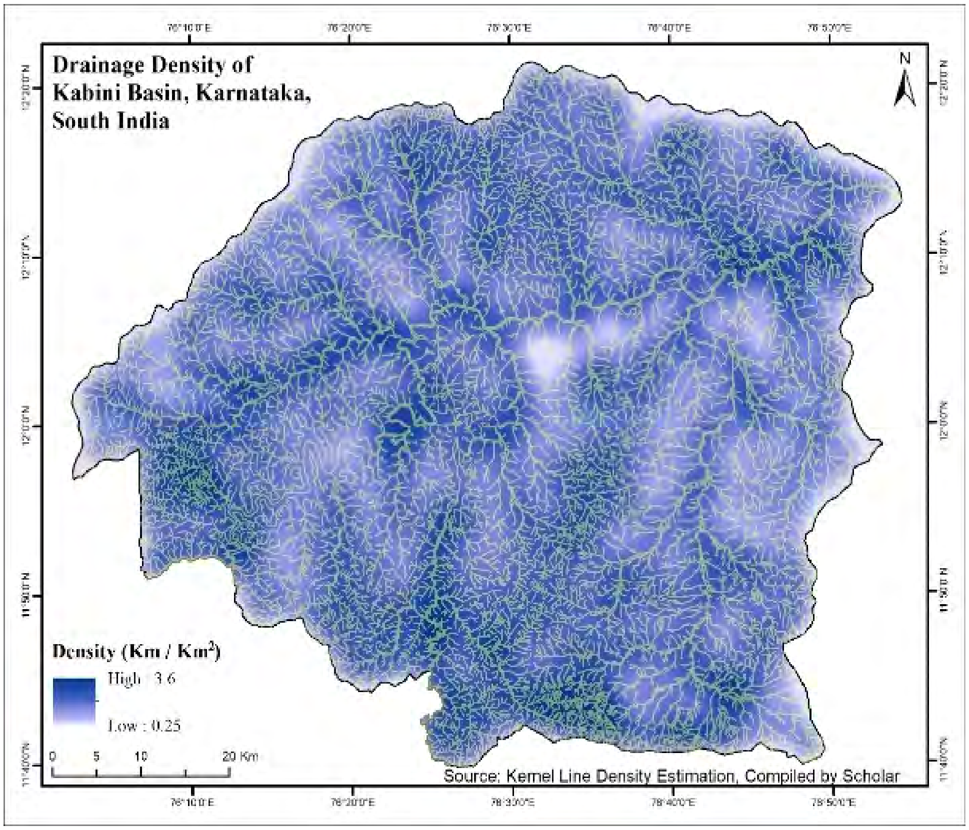


FIGURE 10 Drainage Density

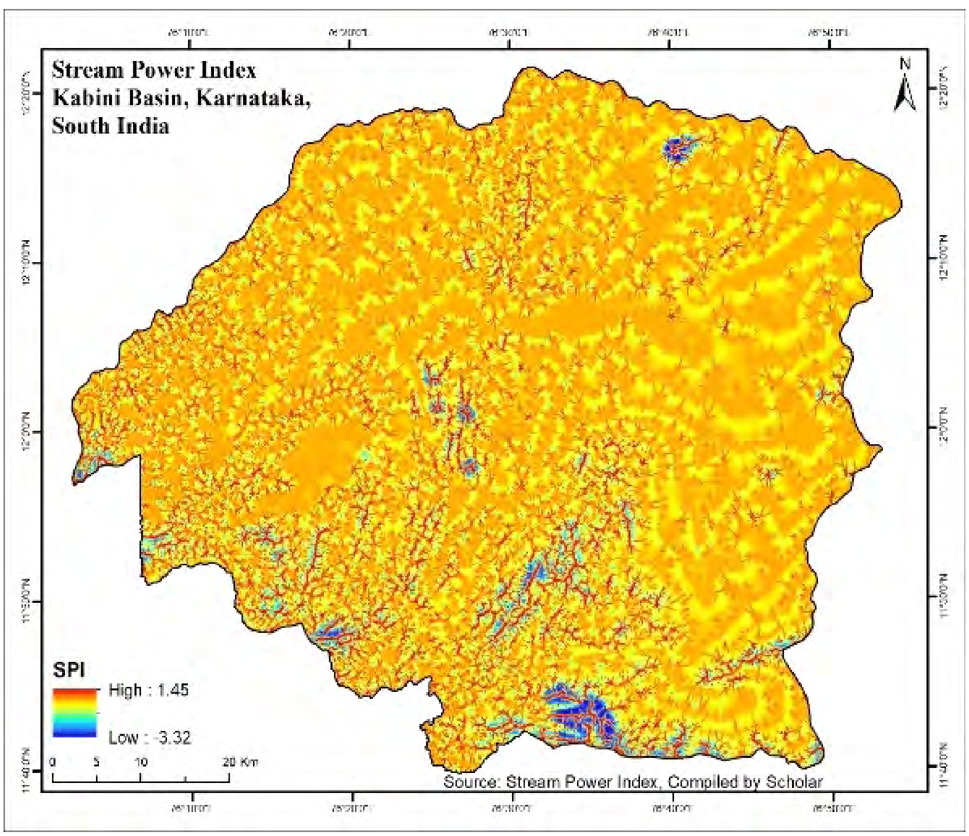


FIGURE 11 Stream Power Index

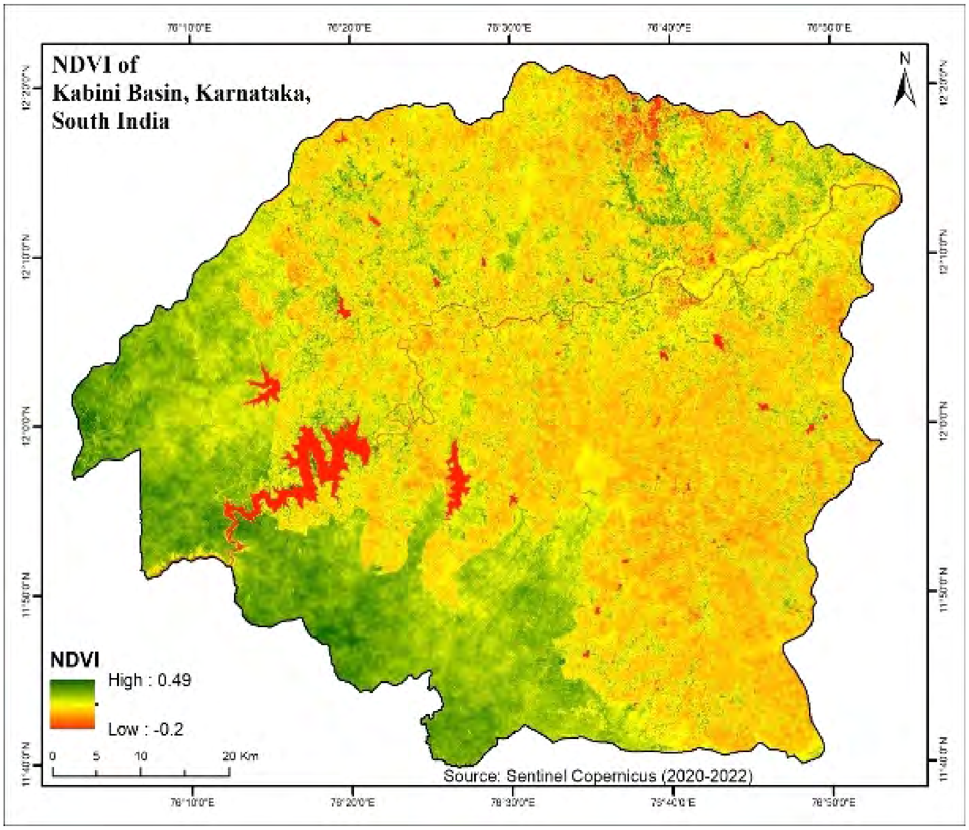


FIGURE 12 NDVI

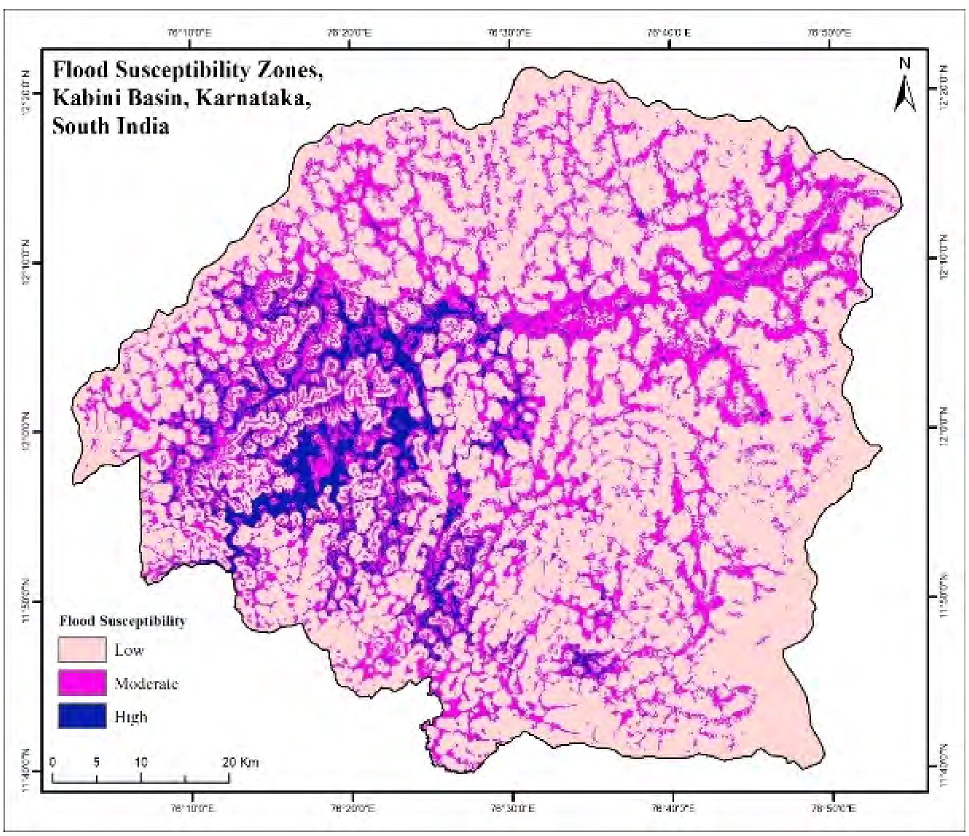


FIGURE 13 Flood Susceptibility

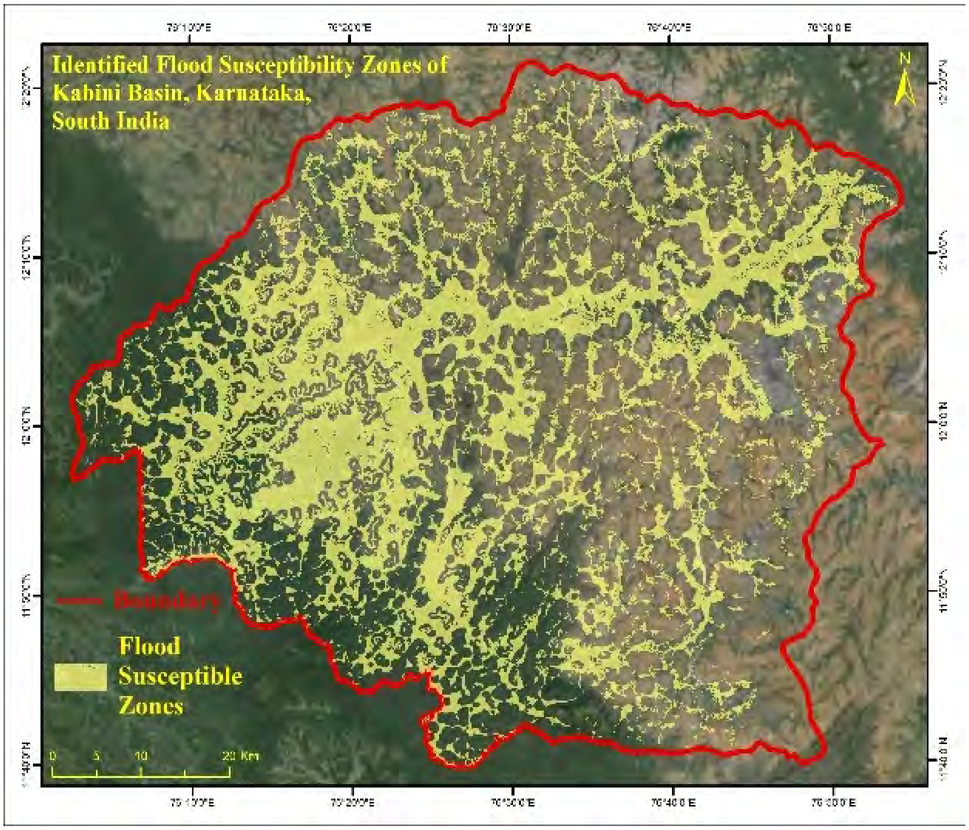


FIGURE 14 **Flood Susceptibility Zones**

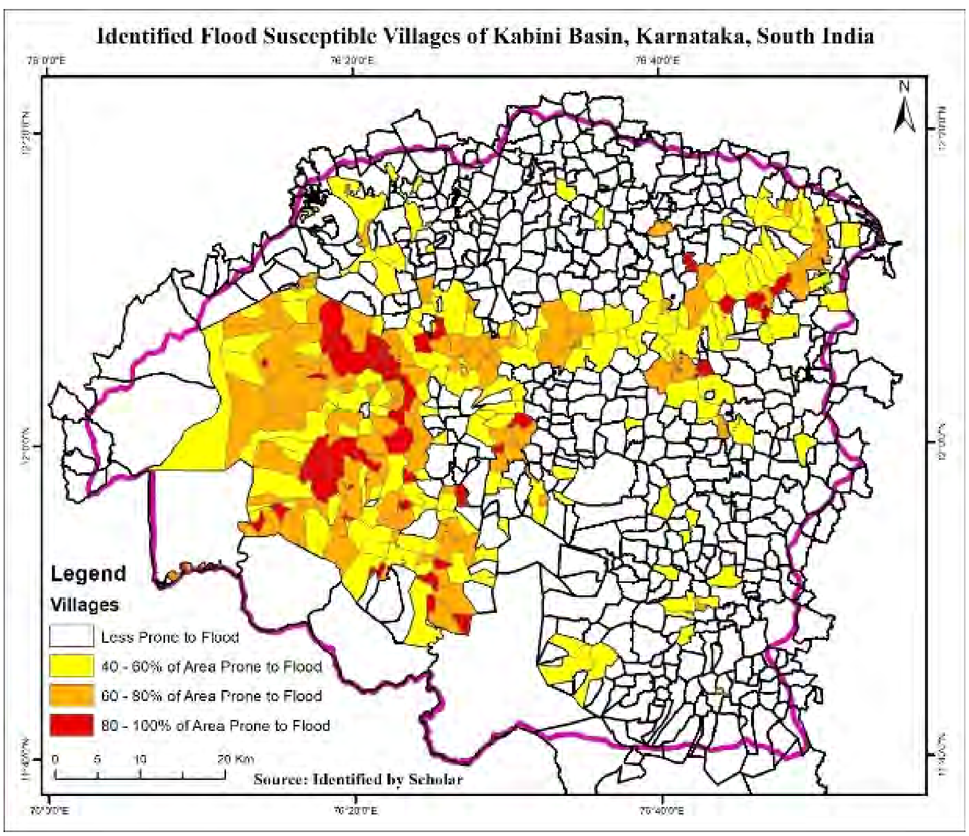


FIGURE 15 **Flood Susceptible Villages**

Similarly, the Kabini basin flood assessment categorized 946 villages into varying susceptibility levels, with 80 villages identified as highly vulnerable to flooding. This alignment with the specific inundation patterns observed in Nanjangud provides a solid basis for validating the Kabini basin flood susceptibility classifications, particularly for high-risk areas.

3.10 | Discussion

Numerous approaches have been used in the considerable study on flood susceptibility mapping, with notable similarities in the methods and results between studies. A recurring topic is the incorporation of various techniques to improve the precision and dependability of flood maps. Data, both spatial and non-spatial, were gathered from multiple sources. Selection of flood influencing factors were identified through average annual rainfall, rainfall runoff, elevation, slope, TWI, TPI, DD, STPI and NDVI.

Using a MCDM technique based on Saaty's AHP's Relative Importance, each component was standardized and given a weight according to its impact on flooding. Each raster data set was given a relative weight using weight assignment techniques, and different flood impacting elements were integrated using a weighted product model. The current study used the WGM, which is selectively chosen, to create the flood hazard maps.

A total of 80 villages were found to be extremely vulnerable to flooding out of the 946 communities that were divided into different susceptibility levels by the Kabini basin flood assessment study.

Further studies with modern techniques combining statistical and machine learning models can improve forecasts of flood susceptibility. The use of ensemble modelling techniques, which integrate several algorithms, has demonstrated potential for enhancing the resilience of flood susceptibility maps. The ability of artificial intelligence to improve flood prediction models is further demonstrated by the integration of swarm intelligence algorithms into neural fuzzy-based machine learning ensembles and deep learning neural networks can enhance the accuracy of flood susceptibility maps.

4 | CONCLUSIONS

An extensive study of flood susceptibility across 946 villages in Mysore and Chamarajanagara districts reveals varying levels of flood vulnerability. Among these villages, 587 are classified as having low susceptibility to floods, 163 as less susceptible, 116 as moderately susceptible, and 80 as highly susceptible. Factors such as rainfall intensity, soil moisture, elevation, slope, topographic indices, drainage characteristics, and vegetation cover were analyzed comprehensively to understand the underlying vulnerabilities. The study emphasizes the importance of adopting multi-dimensional approaches in flood susceptibility mapping. This approach highlights the complex interactions contributing to flood susceptibility, enabling better-informed decision-making and targeted interventions. Several measures are recommended to mitigate flood risks effectively in these vulnerable areas. Firstly, implementing robust land use planning strategies that consider flood risk in urban and rural development plans can help reduce exposure to flood hazards. Secondly, it is crucial to enhance drainage infrastructure to improve its capacity and efficiency in managing increased water flow during heavy rainfall events. Also, promoting sustainable agricultural practices that minimize soil erosion and improve water retention can help reduce runoff and alleviate flood impacts.

CONFLICT OF INTEREST

The author(s) declares no conflict of interest.

AUTHOR'S CONTRIBUTION

Alec Lobo: Conceptualization, Methodology, Data Curation, Writing-review and editing, Writing original draft. P. Madesh: Supervision, Validation, Visualization, Writing-review and editing.

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