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Advancing Flood Risk Assessment through Integrated Hazard Mapping: A Google Earth Engine-Based Approach for Comprehensive Scientific Analysis and Decision Support

Rajat Agrawal[1], Suraj Kumar Singh[1], Shruti Kanga[2], Bhartendu Sajan[1], Gowhar Meraj[3] and Pankaj Kumar[4]*

[1]Centre for Climate Change and Water Research, Suresh Gyan Vihar University, Jaipur − 302017, Rajasthan, India
[2]Department of Geography, School of Environment and Earth Sciences, Central University of Punjab
Bhatinda − 151401, Punjab, India
[3]Department of Ecosystem Studies, Graduate School of Agricultural and Life Sciences, The University of Tokyo
Tokyo − 113-8654, Japan
[4]Institute for Global Environmental Strategies, Hayama − 240-0115, Japan
✉ kumar@iges.or.jp

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Abstract: This study utilises a comprehensive, multi-layered approach to assess flooding susceptibility in a specific area, integrating diverse environmental datasets such as JRC Global Surface Water, Landsat 8 images, and SRTM elevation data. Employing the GEE FMA, a powerful tool leveraging Google Earth Engine capabilities, the analysis covers water occurrence, permanent water, elevation, distance to water, topographic hazard score, and vegetation indices (NDVI and NDWI). The Water Occurrence layer establishes a foundational understanding of water-body distribution's correlation with flood vulnerability, while Permanent Water refines this understanding. Distance to Water measures proximity for targeted risk evaluation, and Elevation identifies vulnerable regions based on topography. The GEE FMA synthesises these layers into a Flood Hazard Susceptibility map, categorising vulnerability into Very Low, Low, Medium, High, and Very High. This nuanced understanding is crucial for prioritising interventions. The GEE FMA's rapid processing speed makes it an invaluable tool for short-term decision support in flood hazard disaster management, offering insights for informed decision-making and resilient infrastructure development. The Topographic Hazard Score provides information on how topography influences flood risk, while the Wetness Hazard Score categorises moisture conditions for identifying flood-prone locations. Decision-makers rely on these values for quick and precise flood susceptibility assessments. In an era of climate uncertainties and urbanisation, the GEE FMA emerges as a reliable tool for decision-making, mitigating flood impacts, and developing effective flood risk management strategies.

Keywords: Flood hazard assessment; Google earth engine; Multi-layered analysis; Decision support system; Disaster management.

Introduction

Floods pose a severe threat to the world as a common natural disaster since they can potentially do significant damage. Numerous things, such as intense rain, storm surges, river overflow, or quick snowmelt, might cause these occurrences. Beyond just physically damaging infrastructure, floods can affect communities, upend

*Corresponding Author

ecosystems, and frequently have long-term negative social and economic repercussions (Perera et al., 2019; Podlaha et al., 2018). Because of the effects of urbanisation, flood risk is increased in metropolitan areas. Cities that expand quickly change the way land is used add more impervious surfaces and disrupt natural drainage patterns. Due to these changes, urban areas are more vulnerable to flooding, which calls for a sophisticated strategy to manage the risks involved (IFRC, n.d.).

Flood susceptibility is increased because roads and structures, which were before permeable, are now impervious due to urbanisation. Because of this modification, the land's inherent ability to absorb precipitation is diminished, increasing flow during periods of heavy rainfall. Metropolitan areas are more vulnerable to floods due to the concentration of people and valuable goods (Coumou and Rahmstorf, 2012, Werner, 2004). This can lead to severe economic and social consequences. Effective risk management necessitates a thorough understanding of the intricate interplay of environmental, societal, and infrastructure elements contributing to urban flood risk(Di Baldassarre et al., 2009). An essential first step in lessening the effects of floods is to analyse the flood risk. This entails thoroughly examining variables such as geography, rainfall patterns, land use, river morphology, and protective infrastructure. These complex dynamics present particular difficulties for risk management and disaster resilience in the urban setting (Preistnall et al., 2000; Galland et al., 1991). Inadequate flood risk evaluation in urban areas can lead to adverse health effects, population displacement, economic losses, and disruption of vital services. It is, therefore, essential to approach flood risk assessment from a holistic and multidisciplinary perspective (Sinha et al., 1998).

In-depth approaches to assessing flood risk are essential for tackling the complex issues that urban floods present. These techniques incorporate several characteristics and use cutting-edge technologies for modeling, mapping, and analysing flood-prone areas (Wing et al., 2018). It takes a multidisciplinary approach involving knowledge of hydrology, meteorology, geospatial analysis, and risk modeling to comprehend the complexity of urban flood risk fully. The creative use of Google Earth Engine (GEE) for integrated danger mapping is helpful in this context (McLearn 2019; Institute of Catastrophic Loss Reduction, 2019). The comprehensive evaluation of flood dangers in urban settings is made possible by the effective processing of large-scale geospatial data, which is made possible by GEE's capabilities. This strategy offers decision-makers and stakeholders in disaster management and urban planning meaningful insights to improve resilience in urban flood concerns (Perera et al., 2000).

Recent studies on urban floods and flood risk assessment have greatly improved our knowledge of these intricate processes. Recent research has strongly emphasised figuring out the complex effects of climate change on flood patterns (Lewis et al., 2016). To improve the predictive accuracy of assessments, especially in urban areas, researchers have emphasised how vital it is to incorporate predicted fluctuations in precipitation and extreme weather events into flood risk models (Bhola et al., 2020; Allen et al., 2018). This focus on changes brought about by climate change emphasises how dynamic flood threats are and how vital adaptive approaches are.

In recent studies, the influence of urbanisation in increasing flood susceptibility has been thoroughly examined. Scholars have examined the complex relationships between land-use changes and urbanisation and how they affect regional hydrology (Mustafa and Szydłowski, 2021). These findings emphasise the significance of comprehending the dynamics of urbanization and its influence on flood risks. These kinds of insights are essential for developing practical flood mitigation methods in rapidly urbanising areas, where striking a careful balance between infrastructural expansion and environmental resilience is critical (Attari and Hosseini, 2019).

Technological advancements and the development of geospatial analysis tools have brought about a new era for flood risk assessment approaches. To improve the accuracy of flood hazard mapping, recent research examines the combination of cutting-edge technology such as machine learning methods, high-resolution modelling, and remote sensing data (Chang et al., 2018). By combining a variety of datasets and enhancing the spatial resolution of hazard mapping, this method expands the scope of flood risk assessments. It offers a more thorough grasp of the nuances of urban flood risk (Pal and Singha, 2021). These technological advancements could completely transform the effectiveness and precision of flood risk assessments in urban settings.

In recent flood risk assessment studies, Google Earth Engine (GEE) has become a critical platform that provides researchers with a powerful tool for processing and analysing large-scale geospatial data. GEE's ability to smoothly integrate a variety of datasets, including topography data, hydro-environmental indices, and satellite imagery, has been proven by recent field applications (Yusoff et al., 2021). This integration demonstrates how GEE can improve and expedite flood risk assessment procedures by enabling the creation of precise and current flood hazard maps. The technology is positioned to revolutionise flood risk assessment because it can effectively manage large datasets (Jain et al., 2016).

The aim of this study is to improve flood risk assessment by integrating geospatial analysis, Google Earth Engine, and the latest technological advancements. Our primary objective is to understand the dynamics of urban flood risk and evaluate the efficiency of GEE in streamlining the flood risk assessment process (Amin et al., 2018). We aspire to provide valuable insights to stakeholders and decision-makers in urban planning and crisis management. Our study strives to bridge the gap between conventional and modern approaches to develop more efficient and resilient methods for managing and reducing the impact of urban floods (Tena et al., 2019).

Materials and Methods

Study Area

The Jaipur District, situated in the western part of India in the state of Rajasthan, spans an area of 11,143 square kilometers, which accounts for about 3.23% of the total area of the state. Nestled between the latitudes 26°25' N and 27°51' N and the longitudes 74° 55' E and 76° 15' E, this district is home to Jaipur, the state capital, also fondly known as the Pink City. The district is situated in the foothills of the Aravali range, bordered by hills in the north and east, and expansive plains in the west and south. The district stretches approximately 180 kilometers from east to west and about 110 kilometres from north to south.

Jaipur District is surrounded by various districts and a state: Nagaur District to the northwest, Sikar District to the north, the state of Haryana to the far northeast, Tonk District to the south, SawaiMadhopur District to the southeast, Ajmer District to the west, and Alwar and Dausa districts to the east.

As per the 2011 census, the district has a population of 6,626,178, resulting in a population density of about 598 per square kilometre, or 1,550 per square mile. The intricate tapestry of Jaipur District's geographical layout provides a unique environmental and sociocultural context that shapes the patterns and impacts of natural disasters such as floods. right bank. It passes through Fatehabad, Modhapur, and Bharatpur and ends at Yamuna. Jamwa Ramgarh dam has been built across the river in Jaipur's periphery. The variation of height from sea level at different locations of the district is 122 to 431 m. Figure 1 shows the location map of the study area.

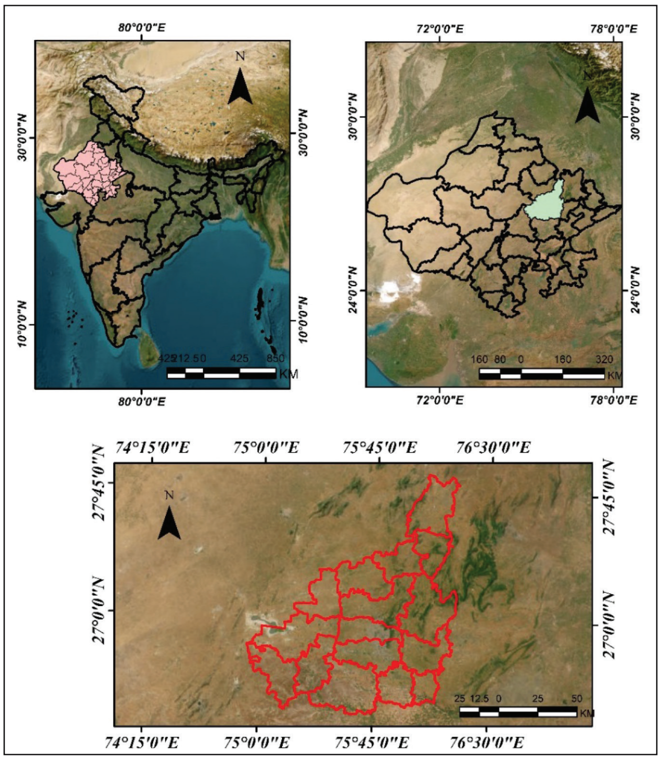

Figure 1: Location map of study area.

Methodology

Water Occurrence Layer

This layer provides a detailed representation of the distribution of water bodies worldwide, using data from remote sensing to map the location and size of water features such as rivers, lakes, and reservoirs. It is generated from the JRC Global Surface Water dataset and establishes a baseline understanding of the geographical distribution of water. This knowledge is crucial for flood risk assessment, as the existence and size of water bodies greatly influence an area's overall vulnerability to floods. By highlighting areas where the likelihood of flooding is correlated with the presence of water features, this layer establishes the foundation for further investigations (Babaei et al., 2018).

Permanent Water Layer

This layer builds on the Water Occurrence layer and is primarily concerned with locating bodies of water with long-lasting features, like rivers, lakes, and reservoirs. It adds a temporal component to flood risk assessment by differentiating between transient and permanent water features. Identifying regions where flood risk management methods should be prioritised is easier by knowing the spatial distribution of permanent water bodies, which greatly influence the long-term dynamics of floods (Zeng et al., 2020). This layer improves the accuracy of flood risk assessment by isolating these aspects, allowing for a more sophisticated comprehension of the enduring elements that contribute to vulnerability.

Distance from Stream

Using a quick distance transform method, this layer measures how close a location is to a permanent body of water. This geographical metric is essential for determining the proximity of permanent water sources to places that could flood. Higher numbers on the layer's distance score gradient indicate sites that are further away from permanent water bodies. This knowledge makes prioritization of intervention techniques and the development of infrastructure possible, which is crucial for decision-making. It establishes a thorough spatial hierarchy of flood susceptibility, which successfully directs the use of resources and risk mitigation measures.

Wetness Hazard Score

One important tool for assessing the moisture content of the terrain and identifying places that could flood is the Wetness Hazard Score, which is used in flood hazard mapping. The Normalised Difference Water Index (NDWI) in the code, which evaluates the presence of water by examining reflectance values in the green and near-infrared spectral bands, is the source of this score (Katiyar et al., 2021). Based on the determined wetness conditions, the resulting Wetness Hazard Score divides the landscape into five levels, from very low to very high. The layer's technique takes into account NDWI measurements and uses a systematic scoring approach to identify places that have higher moisture content and are therefore more likely to flood. Since the Wetness Hazard Score highlights areas with higher water content that could make flood dangers worse, it plays a critical role in determining flood susceptibility evaluation. Furthermore, adding this layer to the overall mapping of flood hazards, improves the precision of flood risk assessments, assisting in the efficient formulation of flood mitigation and management plans. Thus, the Wetness Hazard Score's methodological integration is crucial to comprehending the landscape's moisture dynamics and how they affect people's sensitivity to flood hazards (Moniruzzaman et al., 2021).

Elevation Layer

This layer provides essential information on the topographical relief of the research area by utilising elevation data from the Shuttle Radar Topography Mission (SRTM). Since low-lying locations are frequently more vulnerable to flooding during periods of excessive rainfall or storm activity, elevation is a major factor influencing flooding. This layer serves as a fundamental component of flood risk assessment by helping identify locations susceptible to flooding. Comprehending the differences in elevation is crucial for pinpointing areas more vulnerable to flooding and facilitates thorough mapping of hazards. Because the Elevation layer considers the topographic context of the environment, it adds a crucial dimension to the vulnerability to flooding.

Topographic Position Index (TPI)

Using the elevation data, the Topographic Position Index (TPI) layer is created, which helps in comprehending regional topographical variances. TPI values help describe the topographical context of the terrain, whether they are positive (signaling ridge features) or negative (signaling valley features). This layer considers the impact of topographical factors on possible flood scenarios, giving flood hazard assessment a more nuanced perspective. TPI offers essential insights into how landscape morphology may affect water flow and buildup, increasing the risk of flooding. A thorough understanding of the topographic position is necessary for assessing flood risk.

Topographic Hazard Score

A key component of flood hazard mapping is the Topographic Hazard Score, which is produced from the Topographic Position Index (TPI) layer and captures subtle topographical details that affect flood scenarios. TPI values highlight the complex link between landscape morphology and water dynamics and offer vital insights into regional topographical variations, whether they are positive (showing ridges) or negative (indicating valleys) (Meraj et al., 2015). One essential component of the flood hazard mapping process is the Topographic Hazard Score, which provides a thorough understanding of flood risk by taking into account the influence of topographical elements on hypothetical flood scenarios. The Google Earth Engine (GEE) code's effectiveness in handling and evaluating massive amounts of geospatial data quickly highlights its capacity to enable a quick and precise evaluation of topographic factors influencing flood susceptibility, which helps with well-informed decision-making regarding flood mitigation and management (Bera et al., 2021).

Vegetation Indices (NDVI and NDWI)
The algorithm computes the Normalised Difference Vegetation Index (NDVI) and the Normalised Difference Water Index (NDWI) using Landsat 8 images. NDVI reflects the density of healthy vegetation, which adds to the vegetation danger score. NDWI emphasises water content, influencing the wetness hazard score. These indexes link vegetation health and water content to flood susceptibility, providing crucial environmental data. The NDVI provides information on land cover, possible runoff characteristics, and the health and density of vegetation. Conversely, NDWI highlights places with high water content, such as open water bodies and saturated soils. When taken as a whole, these layers provide information on the ecological features of the region, giving flood risk assessment an environmental framework. Figure 2 shows the Methodology flow chart used in this study.

Results

Flood Influencing Factors

In this study, a comprehensive flood hazard assessment was conducted using a multi-layered approach, integrating various environmental parameters to evaluate the susceptibility of the study area to flooding. The initial water occurrence layer provided a foundational understanding of the spatial distribution of water bodies, emphasising permanent water features as potential risk factors. The subsequent Distance from the Permanent Water layer refined this analysis, pinpointing areas in close proximity to these sources for targeted risk assessment. Elevation data, coupled with its hazard score, identified regions at differing elevations, crucial for understanding inundation dynamics. The Topographic Position Index (TPI) layer introduced a topographical perspective, capturing the influence of terrain on flood vulnerability. Vegetation indices, including NDVI and NDWI, contributed further by considering the role of vegetation health and water

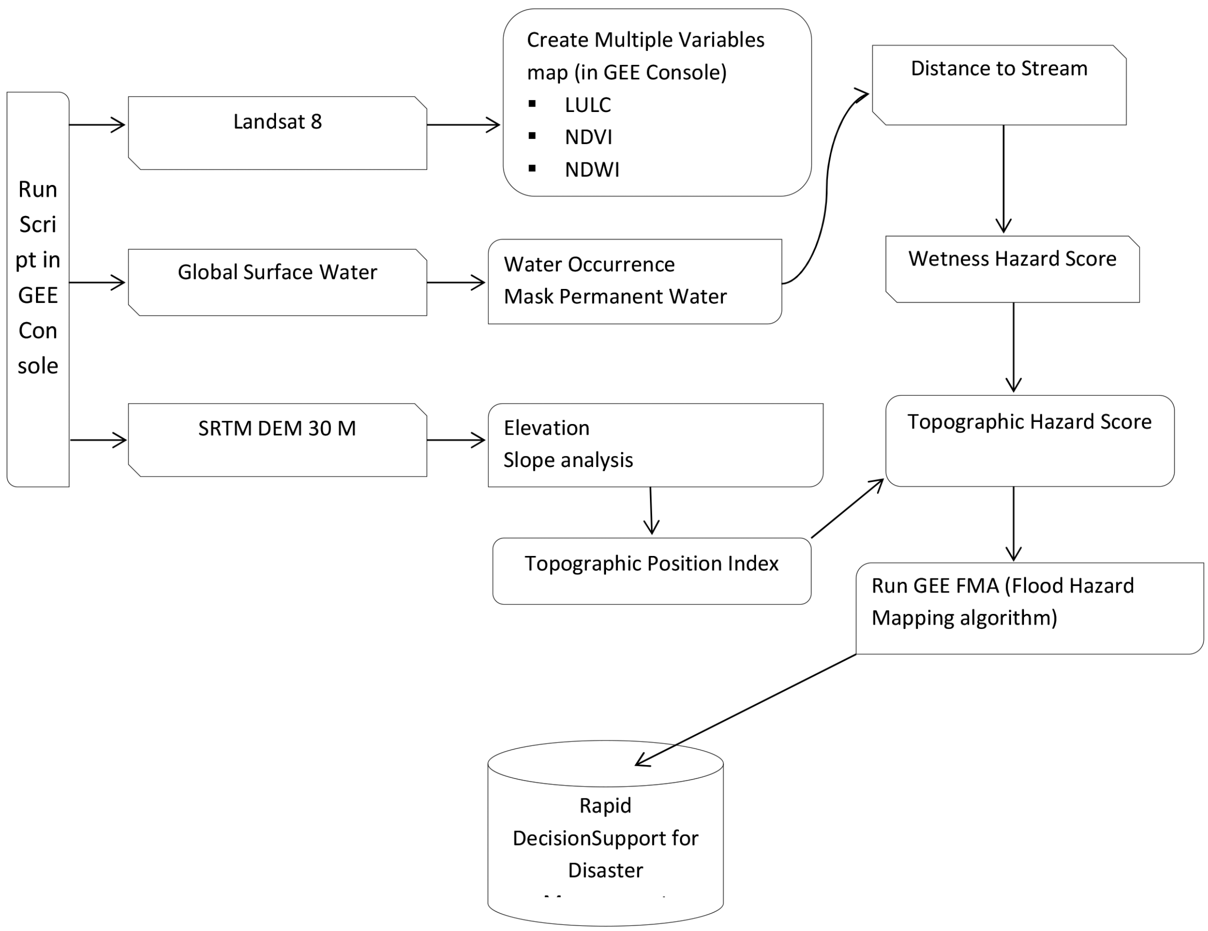

Figure 2: Methodology flow chart.

content in flood susceptibility. High NDVI values indicated robust vegetation, potentially mitigating flood impacts, while NDWI identified areas with high water content contributing to wetness hazard. The Flood Hazard layer synthesised scores from each contributing layer, providing a comprehensive and quantitative measure of flood susceptibility. This integrated approach considered diverse environmental factors, offering a nuanced understanding of the spatial distribution of flood risk. The statistical amalgamation of these layers enabled the identification of high-risk zones, facilitating targeted urban planning and disaster management efforts. Each layer, from water occurrence to topography, played a crucial role in the overall flood hazard score, making this holistic approach invaluable for informed decision-making and resilient infrastructure development in flood-prone areas.

Slope Map

In flood modeling, the slope is a significant factor that directly influences the speed and volume of water runoff, determining the severity and extent of flooding within a given region. Locations with steep slopes can accelerate water flow downhill, thus increasing the risk of flash floods and erosion. Conversely, flat terrain often leads to water logging, making low-gradient slopes more susceptible to flooding than high-gradient ones. Our study utilised a slope map divided into five classes of varying degrees. As illustrated in Figure 3, a substantial area of the Jaipur district has a slope ranging from 0 to 4.08 degrees, implying that the region predominantly comprises flat terrain. This observation underscores the importance of considering the slope when assessing flood susceptibility. Our results affirm that flood-prone areas are primarily situated in flat and low-elevation zones, where the potential for rapid water flow is minimised due to the landscape's rough texture. Consequently, the study further emphasises that understanding the slope dynamics is crucial for flood modeling and devising effective flood management strategies.

Permanent Water

Permanent water bodies play a crucial role in flood risk assessment, serving as a key indicator of potential inundation areas. In our study, the analysis of permanent water bodies involved the utilization of the Global Surface Water dataset shown in Figure 4. This dataset provides information on the occurrence of water throughout the year, enabling the identification of regions with consistent water presence. The

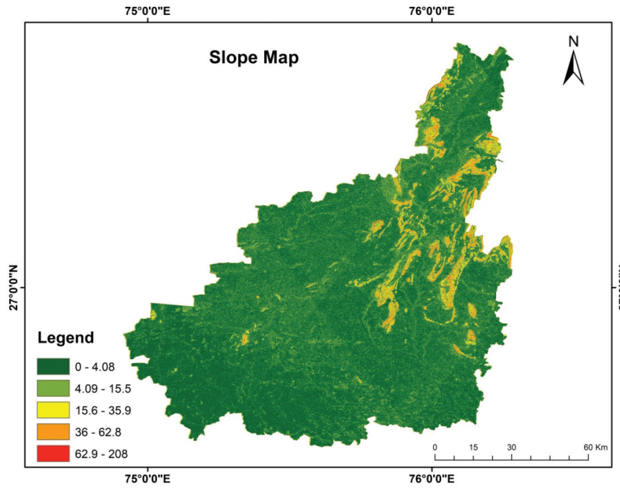

Figure 3: Slope map.

identification of permanent water bodies is particularly relevant in flood hazard mapping as they represent areas prone to recurrent flooding. By employing a threshold of 80% occurrence, we classified regions with persistent water presence as permanent water bodies. As illustrated in the results, these areas are depicted in a distinct blue palette in Figure 4, emphasising their significance in the flood hazard landscape. Permanent water bodies contribute significantly to flood susceptibility, acting as focal points for potential inundation and influencing the surrounding terrain's vulnerability. The delineation of these water bodies provides valuable insights into areas with heightened flood risk, guiding the formulation of targeted mitigation strategies. Moreover, the integration of permanent water data into the hazard mapping process enhances the accuracy of flood risk assessments, allowing for a more comprehensive understanding of the dynamic interplay between water bodies and the surrounding landscape. In conclusion, the consideration of permanent water bodies as a parameter in flood hazard mapping proves instrumental in identifying high-risk zones and refining strategies for effective flood risk management.

Distances to Stream

The distance to stream parameter in our flood hazard assessment involves evaluating the proximity of a location to permanent water bodies, indicating the potential reach of flooding in the surrounding areas shown in Figure 5. Using the Fast Distance Transform algorithm, we quantified this distance, with the resulting map showcasing varying proximity levels in a spectrum of colours. Areas closer to permanent water bodies are depicted in warm tones, gradually transitioning to cooler tones as the distance increases. The significance of the

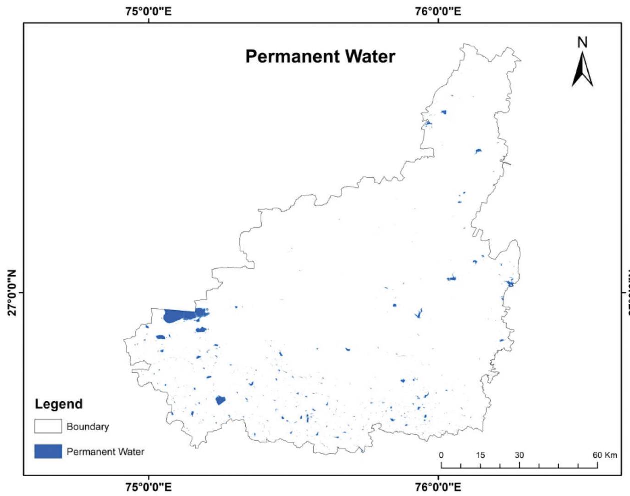

Figure 4: Permanent stagnate water.

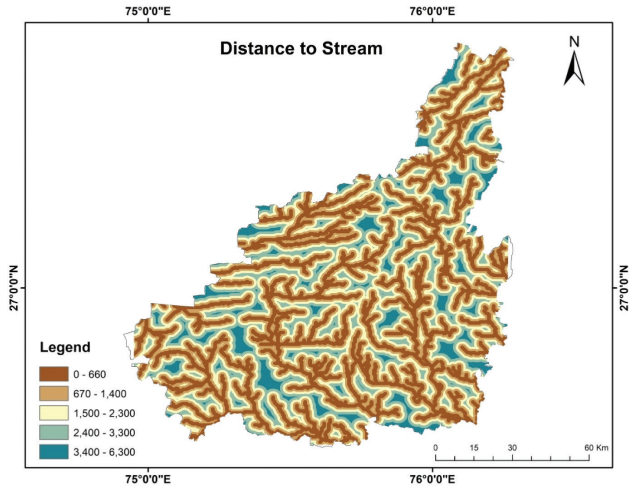

Figure 5: Distances to stream.

distance to water parameter lies in its ability to identify zones at different risk levels based on their proximity to water bodies. Closer proximity implies a higher likelihood of flooding, while greater distance suggests a lower risk. In our hazard mapping, we divided the distance into five hazard score categories, ranging from 1 (closest) to 5 (farthest). This categorisation aids in clearly demarcating areas with distinct flood risk levels. The distance to the water parameter is crucial for flood hazard assessment as it delineates vulnerable regions susceptible to inundation. It serves as a foundational layer for understanding the spatial distribution of flood risk, enabling stakeholders to prioritise intervention strategies in areas with higher susceptibility. This parameter also facilitates a nuanced analysis, allowing for targeted planning and resource allocation based on the varying degrees of proximity to water bodies. Overall, the distance to water parameter enhances the precision of flood hazard mapping by incorporating the spatial relationship between permanent water bodies and the surrounding landscape.

Elevation

Elevation plays a crucial role in flood modelling due to its significant impact on the water flow during a flood event. The natural topography of the land directs water from higher to lower elevations shown in Figure 6. Consequently, areas with lower elevations are at a higher risk of flood impact, as they are more susceptible to water inundation. Conversely, areas with higher elevations are less likely to face the brunt of floods, as water tends to flow away from such regions. In flood modelling, data on elevation is leveraged to create digital elevation models (DEMs), providing a comprehensive representation of the land surface's topography. In this study, we utilised an elevation map divided into five classes illustrated in Figure 6, computed using Landsat-8 OLI imagery with a resolution of 30 m. This map helped us understand the distribution of various regional elevations and their correlation with flood susceptibility. The findings underscore the importance of considering elevation in flood modeling and developing flood management strategies.

Land Use Land Cover (LULC)

Land use/Land cover is considered as one of the most important influencing factors to identify areas, which are vulnerable to be inundated by flooding. Land use impacts some hydrological process components such as evapotranspiration, infiltration, and runoff generation. LULC is considered the most important component for flood susceptibility as it represents the current usage of the land, its form and nature, and its value relative to soil stability and infiltration. When it rains in the region, the rainfall amount that passes in the rivers depends on the circumstances of the area, landscape, and LU/LC. Land Covers, such as permanent grassland or other crops, significantly impact the soil's capacity to store water. Rainfall-runoff is far more common on bare land than it does in regions with a dense layer of vegetation. Rich vegetation lowers runoff by delaying rainfall droplets reaching the soil through their lush vegetation body. Conversely, Settlement areas, mostly made of impervious surfaces, cause low water absorption, resulting in higher runoff. The study area's land use/land cover map is prepared using a Sentinel-2 10 m resolution from ESRI Land Cover 2022 dataset downloaded from ESRI ArcGIS (https://livingatlas.

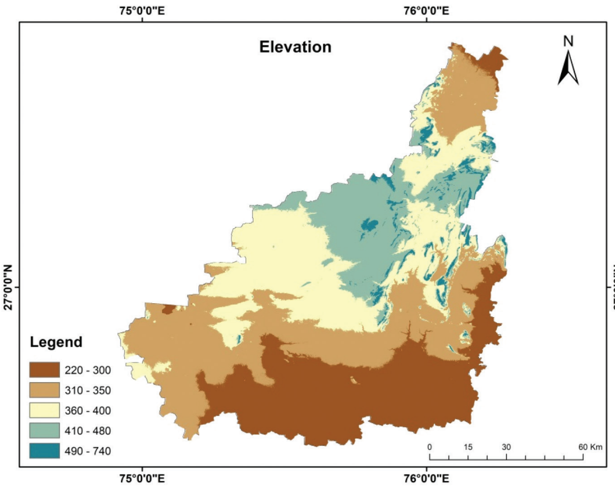

Figure 6: Elevation map.

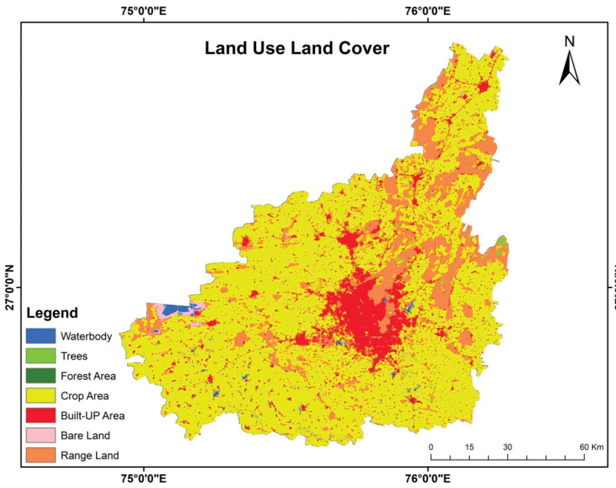

Figure 7: Land use land cover map.

arcgis.com/landcover/). The generated LU/LC map has 7 classes: Water, Trees, Vegetation, Crops, Built Area, Bare Ground, and Rangeland. LULC Map is shown in Figure 7.

Normalised Difference Vegetation Index (NDVI)

Normalised Difference Vegetation Index (NDVI) is a remote sensing technique used in flood modeling to estimate vegetation cover and its impact on water flow. NDVI is a measure of the difference between the amount of red and near-infrared light reflected by vegetation, and it is a useful indicator of vegetation density, health, and productivity.

$$NDVI = (NIR - RED)/(NIr + RED)$$

NIR and RED denote the surface reflectance of the near-infrared and red bands, respectively.

In flood modeling, NDVI data is used to estimate the vegetation cover and its effect on water infiltration and runoff. Vegetation plays a crucial role in regulating the water cycle by intercepting rainfall, enhancing infiltration, and reducing surface runoff. Therefore, the amount and density of vegetation cover can significantly influence the runoff and soil erosion rates in a given area. By analysing NDVI data, an estimation of the amount and density of vegetation cover in an area and how it affects water flow can be generated. For example, NDVI data can be used to estimate the potential impact of land use changes on flooding. If an area is converted from forest to agricultural land, the vegetation cover will be reduced, which can increase the runoff and erosion rates. In this research, the NDVI map with five classes was computed using Landsat-8 OLI imagery with a resolution of 30 m shown in Figure 8.

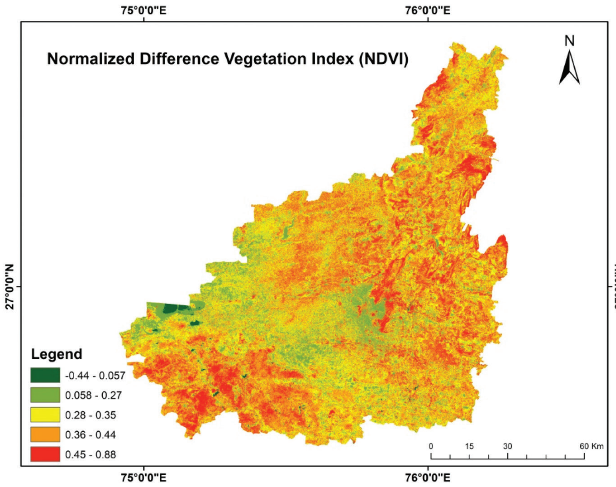

Figure 8: Normalised difference vegetation index (NDVI).

Topographic Position Index (TPI)

The Topographic Position Index (TPI) in the provided flood hazard mapping code is a crucial layer, revealing the elevation characteristics of the terrain in relation to its surroundings. The TPI map, computed by subtracting the local mean elevation from each pixel's elevation, vividly portrays the landscape. Positive values in red signify elevated areas like hills, while negative values in blue represent lower regions such as valleys. Areas with TPI values near zero, depicted in green/white, suggest relatively flat terrain. In the context of flood hazard mapping, high positive TPI indicates shown in Figure 9 have potential barriers to floodwater flow, influencing water accumulation in valleys, while high negative TPI highlights low-lying areas prone to water accumulation during floods. Integrating TPI with distance to water and elevation hazard score provides nuanced insights into how topographic features influence flood vulnerability.

Adjustments to the topographic hazard score based on TPI values enhance the flood hazard map's accuracy, creating a comprehensive understanding of how terrain characteristics contribute to flood susceptibility. Visualising TPI alongside other hazard layers facilitates the identification of areas where topography plays a crucial role in influencing flood risk.

Topographic Hazard Score

The Topographic Hazard Score shown in Figure 10 is a tool used to identify flood hazards by analysing the topographic features of a region. It is based on the Topographic Position Index (TPI) layer, which is classified into five different scores corresponding to different TPI thresholds. The TPI layer helps identify the level of topographic influence on flood hazards by assigning scores to different zones based on their height and slope. For instance, pixels with TPI values greater than 0 are assigned a score of 1, indicating elevated regions or ridges that can potentially reduce the risk of flooding. Transitional zones are marked by TPI values of 2, ranging from 0 to -2. In such zones, scores of 3, 4, and 5 are assigned to TPI intervals -2 to -4, -4 to -6, and below -6, respectively. These intervals correspond to increasingly lower heights, indicating dips or depressions that are more vulnerable to flooding. The Topographic Hazard Score provides a comprehensive evaluation of how terrain shape influences flood risk patterns. By analysing how topographical features from TPI are translated into a visual representation, decision-makers can identify locations vulnerable to water accumulation and elevated flood risk. Decision-makers need to understand the subtleties of Topographic Hazard Scores as they offer significant insights into the topographical aspects that impact flood vulnerability in a given region. The Google Earth Engine (GEE) code's effective translation of these topographic subtleties into a visual representation helps make it easier to identify regions at higher risk of flooding, contributing to better flood hazard mapping and management. Figure 11 illustrates the layout of the code, depicting the spatial distribution of Topographic Hazard Scores and aiding in the interpretation of the results.

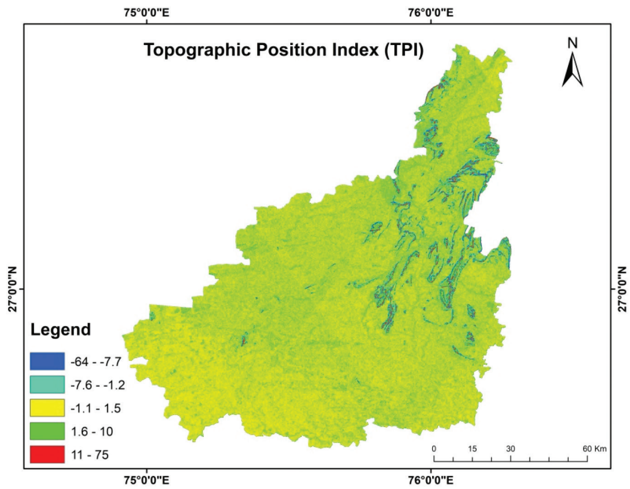

Figure 9: Topographic position index map.

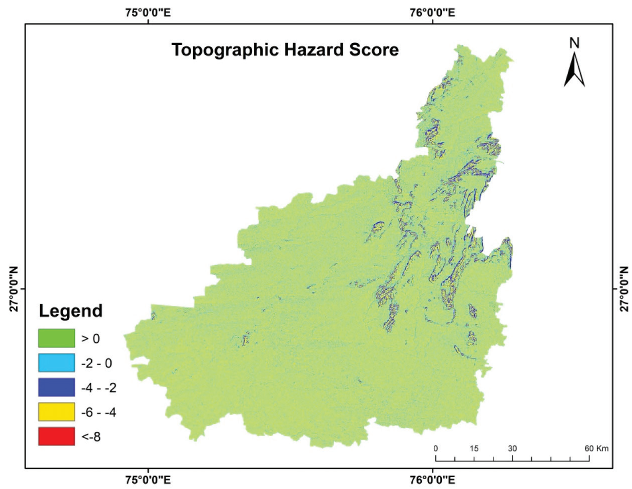

Figure 10: Topographic hazard score map.

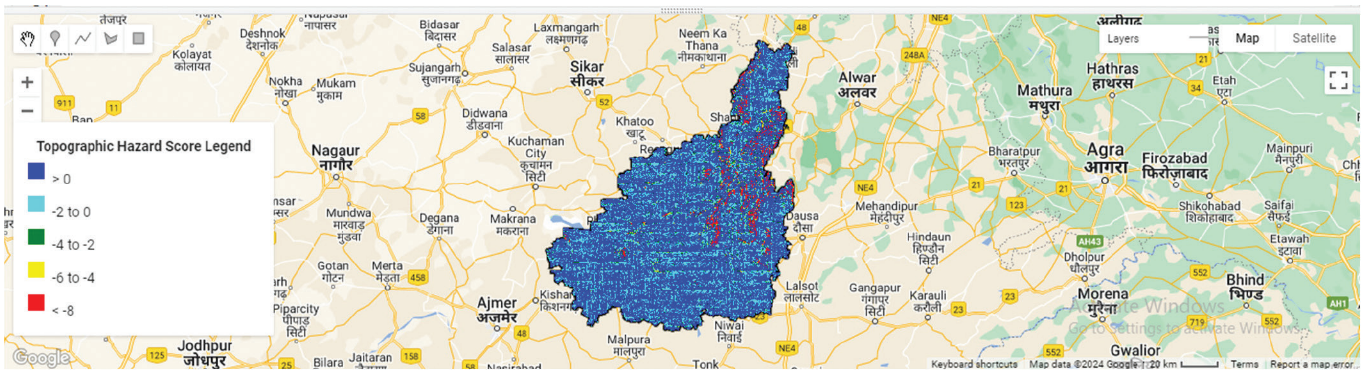

Figure 11: GEE code layout for topographic hazard score.

Wetness Hazard Score

The Wetness Hazard Score—which is produced by the NDWI in the flood hazard mapping code—contributes greatly to the overall evaluation of flood hazards and is essential in determining the moisture conditions of the terrain. The NDWI readings are systematically classified into five categories of moisture hazard for the terrain, which forms the basis of the score. According to the findings, locations with high moisture content (value of 5) are at a higher risk of flooding, whereas areas with a low moisture danger (values of 4, 3, 2, and 1) show progressively lower levels. The highest score is given to locations with NDWI values of more than 0.6, which highlights areas with significant water content. Intermediate scores are given to those with NDWI values between 0.2 and 0.6 and -0.2 and 0.2, which indicate moderate moisture conditions. Additionally, regions with NDWI values less than or equal to -0.6 and between -0.6 and -0.2 are given lower ratings, indicating drier conditions. Higher scores indicate places that are prone to water accumulation, which makes them sensitive to flooding when these wetness hazard scores are correlated with flood susceptibility. On the other hand, areas with lower moisture content and lower scores have a decreased chance of flooding. The Wetness Hazard Score improves the identification and comprehension of places vulnerable to flooding based on moisture dynamics by providing important information to the entire flood hazard mapping approach. In order to reduce the total danger and impact of flooding events, targeted measures in regions with heightened wetness hazard are made possible by this nuanced evaluation, which is essential for effective flood management. Figure 12 shows the Wetness Hazard Score Map and Figure 13 shows GEE layout for Wetness Hazard Score.

Flood Hazard Susceptibility

The final 'Flood Hazard' and 'Flood Hazard Score' layers were created by combining the hazard scores of the many criteria that were taken into account in the flood hazard susceptibility evaluation. The 'Flood Hazard' layer (see Figure 11) is the result of adding together the scores for terrain, vegetation, moisture, elevation, and distance. Every layer adds to the overall evaluation of the region's flood danger. As seen in Figure 12, the 'Flood Hazard Score' layer further refines the assessment by assigning a score to each of the following five categories: Very Low (Score 1), Low (Score 2), Medium (Score 3), High (Score 4), and Very High (Score 5). A more sophisticated understanding of flood vulnerability is made possible by this classification, which supports focused mitigation and management initiatives. First, the "Distance Hazard Score" is used to evaluate the vulnerability of an area to water bodies. A score of 1 denotes low susceptibility, while a score of 5 indicates great susceptibility. The "Topographic Hazard Score" takes into account the

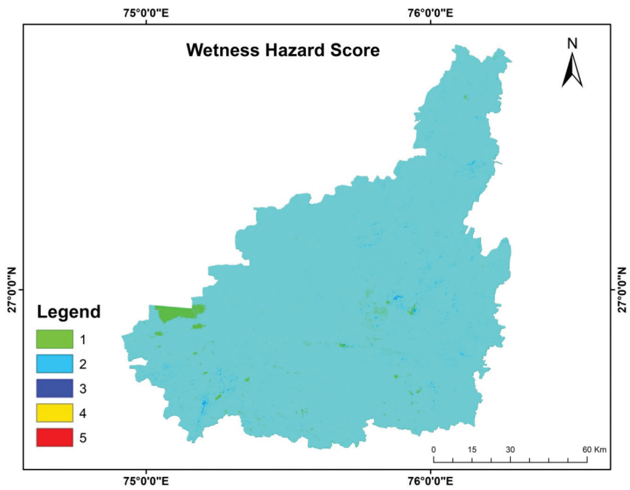

Figure 12: Wetness hazard score.

Figure 13: Layout of code for wetness hazard score.

topography of the area; greater positive scores (up to 5) indicate elevated places that may be less susceptible to flooding, while lower negative values (down to -8) indicate valleys or depressions that are more vulnerable. The effect of vegetation on flooding is measured by the 'Vegetation Hazard Score'. Denser vegetation is indicated by higher ratings (up to 5), which can lower the risk of flooding. The "Wetness Hazard Score" measures the amount of water in the soil; places that score higher (up to 5) are considered to be wetter and more likely to flood. In conclusion, the 'height Hazard Score' takes into account the height of the terrain; higher values (up to 5) denote lower elevations and greater susceptibility. Decision-makers can identify regions that require flood management measures in order of priority by using the combined complete assessment of flood susceptibility provided by the 'Flood Hazard' and 'Flood Hazard Score' layers. By utilising the synergy of numerous characteristics, this approach improves the flood susceptibility assessment's accuracy and applicability. The utilization of Google Earth Engine, which enables quick processing of satellite data and effective computation of hazard scores for well-informed decision-making, adds to the methodology's efficiency. Figure 14 shows the Flood Hazard Susceptibility and Figure 15 shows the GEE code layout for Flood Hazard Susceptibility.

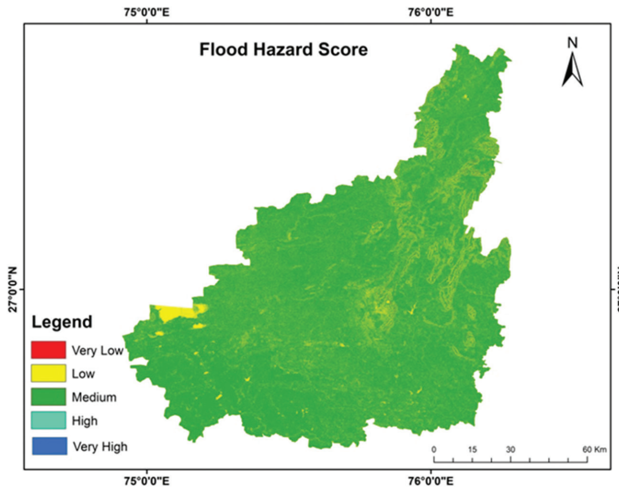

Figure 14: Flood hazard map.

Discussions

This study used a multi-layered strategy for its thorough flood hazard assessment, incorporating multiple environmental parameters to measure how susceptible the study area was to floods. The Water Occurrence layer highlighted permanent water features as potential risk factors and offered a basic grasp of water distribution worldwide. The next layers—Permanent Water, Distance to Water, Elevation, and Topographic Hazard Score—helped to improve this study by taking into account elements including the topography, terrain elevation, and the permanence of water bodies as well as proximity to water (Meraj et al., 2018). By taking into account the water content in flood vulnerability and the quality of the vegetation, the incorporation of vegetation indices (NDVI and NDWI) improved the assessment even further. The NDWI-derived Wetness Hazard Score was important in evaluating the terrain's moisture characteristics, classifying regions into five wetness levels. This careful analysis made a substantial contribution to our understanding of regions that are more likely to accumulate water and experience flooding. The flood hazard assessment gained complexity by taking into account environmental elements such as land use/cover and topography

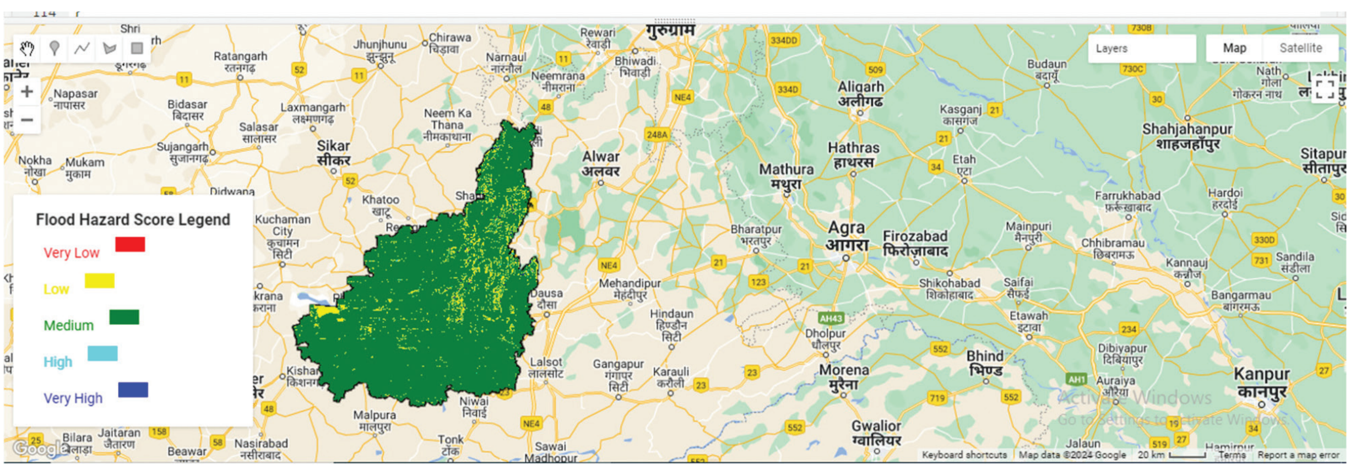

Figure 15: GEE code layout for flood hazard.

characteristics using TPI, topography Hazard Score, and Slope Map. This gave rise to a thorough understanding of susceptibility. The Google Earth Engine (GEE) code demonstrated exceptional speed in processing large amounts of geographical data, allowing for the rapid processing and assessment of different hazard ratings (Vijay et al., 2007). The code's quick analysis of the topography, vegetation, and moisture dynamics allowed for early decision-making about flood control. In addition to processing these various environmental parameters quickly, the GEE code also converted them into visual representations, which helped decision-makers pinpoint high-risk areas and create focused intervention plans. A thorough assessment of flood vulnerability was produced by combining the hazard scores from several factors in the section on flood hazard susceptibility (Vijay et al., 2009). A comprehensive understanding of spatial distribution was made possible by the integration of multiple layers, and a quantitative assessment of vulnerability was provided by the Flood Hazard Score. The evaluation was expedited by using GEE in this process, proving its usefulness in creating decision support systems for flood risk management. The study offered insights into the dynamic interaction of several variables in flood susceptibility and stressed the significance of taking topography, elevation, vegetation, and water distribution into account when discussing specific layers. The GEE code's effectiveness in managing these intricate environmental factors emphasises how important it is for accelerating the procedures involved in making decisions about urban development and flood control (Hussain et al., 2018). To sum up, the comprehensive methodology of the study, in conjunction with the effective use of GEE, makes a substantial contribution to flood hazard mapping and decision support systems. Including a variety of environmental factors improves the accuracy of flood susceptibility evaluations and offers insightful information for developing resilient infrastructure and managing disasters in flood-prone areas.

Conclusion

Using a variety of environmental factors, this study has shown the efficacy of a thorough, multi-layered approach to flood hazard assessment. Water Occurrence, Permanent Water, Elevation, Distance to Water, Topographic Hazard Score, Vegetation Indices, and Wetness Hazard Score have all been integrated to provide a more complex picture of the geographic distribution of flood susceptibility. Simplifying the analysis and decision-making process has been made possible with the help of Google Earth Engine (GEE). Its ability to process large amounts of geographic data efficiently allowed for the quick calculation of hazard scores, which gave important insights into the dynamics of moisture, vegetation, and terrain. This efficiency plays a critical role, especially when it comes to reducing the time required for disaster response and management. This study could lead to better-informed decision support systems for flood risk management, which could have significant future ramifications. Through the integration of many environmental parameters, decision-makers are able to effectively allocate resources, plan robust infrastructure, and prioritise intervention options. These systems are more flexible in reacting to fast-paced and dynamic situations because of the GEE's rapid data processing capability. The knowledge gathered from this study can help with the development of flood mitigation methods in an era of rapidly rising urbanization and climatic uncertainty. Faster and more accurate evaluations are promised by the inclusion of GEE in future disaster management initiatives, enabling prompt decision-making to reduce the impact of floods on vulnerable areas. All things considered, the studies emphasise how important integrated environmental modelling and GEE are to improving our ability to effectively manage and react to floods.

References

Allen, S., Ballesteros-Canovas, J., Randhawa, S., Singha, A., Huggel, C. and Stoffel, M., 2018. Translating the concept of climate risk into an assessment framework to inform adaptation planning: Insights from a pilot study of flood risk in Himachal Pradesh, Northern India. *Environ. Sci. Policy*, **87:** 1-10.

Amin, A., Iqbal, J., Asghar, A. and Ribbe, L., 2018. Analysis of current and future water demands in the upper Indus Basin under IPCC climate and socio-economic scenarios using a hydro-economic WEAP model. *Water*, **10:** 537.

Attari, M. and Hosseini, S.M., 2019. A simple innovative method for calibration of Manning's roughness coefficient in rivers using a similarity concept. *J. Hydrol.*, **575:** 810-823.

Babaei, S., Ghazavi, R. and Erfanian, M., 2018. Urban flood simulation and prioritization of critical urban sub-catchments using SWMM model and PROMETHEE II approach. *Phys. Chem. Earth Parts A/B/C*, **105:** 3-11.

Bhola, P.K., Leandro, J. and Disse, M., 2020. Building hazard maps with differentiated risk perception for flood impact assessment. *Nat. Hazards Earth Syst. Sci*., **20:** 2647-2663.

Bera, A., Taloor, A.K., Meraj, G., Kanga, S., Singh, S.K., Đurin, B. and Anand, S., 2021. Climate vulnerability and economic determinants: Linkages and risk reduction in Sagar Island, India: A geospatial approach. *Quat. Sci. Adv*., **4:** 100038.

Chang, C.-H., Lee, H., Hossain, F., Basnayake, S., Jayasinghe, S., Chishtie, F., Saah, D., Yu, H., Sothea, K. and Du Bui, D., 2018. A model-aided satellite-altimetry-based flood forecasting system for the Mekong River. *Environ. Model. Softw*. **112:** 112-127.

Coumou, D. and Rahmstorf, S., 2012. A decade of weather extremes. *Nat. Clim. Chang*., **2:** 491-496.

Di Baldassarre, G., Schumann, G. and Bates, P.D., 2009. A technique for the calibration of hydraulic models using uncertain satellite observations of flood extent. *J. Hydrol*., **367:** 276-282.

Galland, J.-C., Goutal, N. and Hervouet, J.-M., 1991. TELEMAC: A new numerical model for solving shallow water equations. *Adv. Water Resour.*, **14:** 138-148.

Husain, A., Sharif, M. and Ahmad, M.L., 2018. Simulation of floods in Delhi segment of river Yamuna using HEC-RAS. *Am. J. Water Resour*, **6:** 162-168.

IFRC. 17.5 Million Affected by Floods and Threatened by Disease in South Asia. Available online: https://media.ifrc.org/ifrc/press-release/17-5-million-affected-floods-threatened-disease-south-asia/ (accessed on 20 January 2021).

Institute of Catastrophic Loss Reduction, 2019. Focus on Flood Mapping in Canada; Institute of Catastrophic Loss Reduction: Toronto, ON, Canada.

Jain, M., Dawa, D., Mehta, R., Dimri, A.P. and Pandit, M., 2016. Monitoring land use change and its drivers in Delhi, India using multi-temporal satellite data. *Model. Earth Syst. Environ.*, **2:** 1-14.

Katiyar, V., Tamkuan, N. and Nagai, M., 2021. Near-real-time flood mapping using off-the-shelf models with SAR imagery and deep learning. *Remote Sens*., **13:** 2334.

Lewis, A., Lymburner, L., Purss, M.B.J., Brooke, B., Evans, B., Ip, A., Dekker, A., Irons, J.R., Minchin, S., Mueller, N., et al., 2016. Rapid, high-resolution detection of environmental change over continental scales from satellite data—the Earth Observation Data Cube. *Int. J. Digit. Earth*, **9:** 106-111.

Meraj, G., Khan, T., Romshoo, S.A., Farooq, M., Rohitashw, K. and Sheikh, B.A., 2018. An integrated Geoinformatics and hydrological modelling-based approach for effective flood management in the Jhelum Basin, NW Himalaya. *Proceedings*, **7:** 8.

Meraj, G., Romshoo, S.A., Yousuf, A.R., Altaf, S. and Altaf, F., 2015. Assessing the influence of watershed characteristics on the flood vulnerability of Jhelum basin in Kashmir Himalaya. *Nat. Hazards*, **77:** 153-175.

McLearn, M., 2019. Poor Flood Risk Maps or None at All are Keeping Communities in Flood Prone Areas. *In:* The Globe and Mail. Available online: https://www.theglobeandmail.com/canada/article-poor-flood-risk-maps-or-none-at-all-are-keeping-canadian-communities/ (accessed on 20 January 2021).

Moniruzzaman, M., Thakur, P.K., Kumar, P., Ashraful Alam, M., Garg, V., Rousta, I. and Olafsson, H., 2021. Decadal urban land use/land cover changes and its impact on surface runoff potential for Dhaka City and surroundings using remote sensing. *Remote Sens*., 2021, **13:** 83.

Mustafa, A. and Szydłowski, M., 2021. Application of different building representation techniques in HEC-RAS 2-D for urban flood modeling using the Toce River experimental case. *Peer J*, **9:** e11667.

Pal, S. and Singha, P., Analyzing sensitivity of flood susceptible model in a flood plain river basin. *Geocarto Int.*, **37(24):** 7186-7219

Perera, D., Seidou, O., Agnihotri, J., Mehmood, H. and Rasmy, M., 2020. Challenges and technical advances in flood early warning systems (FEWSs). *In:* Flood Impact Mitigation and Resilience Enhancement; InTech: London, UK.

Perera, D., Seidou, O., Agnihotri, J., Rasmy, M., Smakhtin, V., Coulibaly, P. and Mehmood, H., 2019. Flood early warning systems: A review of benefits, challenges and prospects; United Nations University, Institute for Water, Environment and Health: Hamilton, ON, Canada.

Podlaha, A., Lörinc, M., Bhattacharya, A. and Bowen, S., 2018. Weather, climate & catastrophe insight. *Annu. Rep.*, **1:** 4-10.

Priestnall, G., Jaafar, J. and Duncan, A., 2000. Extracting urban features from LiDAR digital surface models. *Comput. Environ. Urban Syst*., **24:** 65-78.

Sinha, S.K., Sotiropoulos, F. and Odgaard, A.J., 1998. Three-dimensional numerical model for flow through natural rivers. *J. Hydraul. Eng.*, **124:** 13-24.

Tena, T.M., Mwaanga, P. and Nguvulu, A., 2019. Impact of land use/land cover change on hydrological components in Chongwe river catchment. *Sustainability*, **11:** 6415.

Vijay, R., Sargoankar, A. and Gupta, A., 2007. Hydrodynamic simulation of river Yamuna for riverbed assessment: A case study of Delhi region. *Environ. Monit. Assess.*, **130:** 381-387.

Vijay, R., Sargaonkar, A. and Gupta, A., 2009. A hydrodynamic approach to address Yamuna riverbed development in Delhi. *Can. J. Civ. Eng.*, **36:** 1155-1163.

Werner, M.G.F., 2004. A comparison of flood extent modelling approaches through constraining uncertainties on gauge data. *Hydrol. Earth Syst. Sci.*, **8:** 1141-1152.

Wing, O.E.J., Bates, P.D., Smith, A.M., Sampson, C.C., Johnson, K.A., Fargione, J. and Morefield, P., 2018. Estimates of present and future flood risk in the conterminous United States. *Environ. Res. Lett*., **13:** 034023.

Wulder, M.A., Masek, J.G., Cohen, W.B., Loveland, T.R. and Woodcock, C.E., 2012. Opening the archive: How free data has enabled the science and monitoring promise of Landsat. *Remote Sens. Environ.*, **122:** 2-10.

Yusoff, I.M., Ramli, A. and Al-Kasirah, N.A., 2021. Geospatial data and technology application towards managing flood disaster in the context of industrial revolution 4.0 (IR4. 0). *J. Adv. Geospat. Sci. Technol*., **1:** 38-69.

Zeng, Z., Yuan, X., Liang, J. and Li, Y., 2020. Designing and implementing an SWMM-based web service framework to provide decision support for real-time urban storm water management. *Environ. Model. Softw*., **135:** 104887.