



# Mapping flood vulnerability using an analytical hierarchy process (AHP) in the Metropolis of Mumbai

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**Abstract** The burgeoning significance of urban floods in the context of evolving climate dynamics and shifting rainfall patterns underscores the exigency for comprehensive investigation and mitigation strategies. The study employs a multi-criteria assessment (MCE) approach and the analytical hierarchy process (AHP) to evaluate flood-vulnerable zones, wards, and sub-category-wise flood locations in Greater Mumbai. The AHP technique is used to evaluate flood-vulnerable impacting parameters such as rainfall (29.42%), slope (20.96%), land use/land cover (17.52%), vicinity to sewers and storm-water drainage (13.99%), vicinity to natural drainage (8.97%), vegetation (5.58%), and soil (3.56%). The study area is classified under different vulnerable categories as severe vulnerable (46.72%), high to very high (18.74%), and slight to moderate (34.54%). Researchers analysed 234 waterlogged locations, revealing that 85.46% (200 locations) were in the severe to very high vulnerability category, and only 14.52% (34 locations) were in the other three categories. Flood locations are more affected by slope (under the categories of < 5 m and 5.01–10 m), built-up land, sewers

and storm water drainage (< 125 m), natural drainage (< 250 m), rainfall (< 2000 to 2200 mm), lowest dense vegetation, and coastal alluvium in soils. These model-based flood vulnerability maps are crucial for planning flood conservation and mitigation measures.

**Keywords** Urban flooding · Multi-criteria assessment (MCE) · LULC · Vicinity · Waterlogged locations

## Introduction

The newly induced phenomenon of global warming altered the rainfall patterns all over the world (Fowler & Kilsby, 2003; Goswami et al., 2006; Rakhecha & Pisharoty, 1996), which in turn affected city life and often resulted in the stagnation of water in many coastal cities (Guhathakurta & Rajeevan, 2008; Rajeevan et al., 2008), leading to socio-economic impacts and consequences like traffic congestion, a halt to city life, and many more (Ahmadisharaf et al., 2015; He et al., 2007; Rosenzweig et al., 2008). The primary causes of flooding in a region are population growth, fast urbanisation, and changes in river channel morphology brought on by anthropogenic and natural interventions, as well as short-duration heavy rainfall events (Kalnay & Cai, 2003; Lowry, 1977). As a result, the connection between urbanisation and local climate change has caught the interest of many academicians worldwide (Ohashi & Kida,

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2002; Tehrany et al., 2014; Zope et al., 2017). Rapid urbanisation has an impact on land surface qualities (Chen et al., 2006; Lowry, 1977; Mutizwa-Mangiza et al., 2011), which in turn affect diurnal, seasonal, and long-term meteorological and climatic conditions at local, regional, and global scales (Islam & Sado, 2001; Rahmati et al., 2016; Roy et al., 2021). Mumbai is extremely vulnerable to frequent floods during monsoon season because of its unique geographical control, strong building activity, and significant monsoon rainfall (Kadave et al., 2016; Ramesh & Iqbal, 2020; Zope et al., 2017). It is encountering three major types of flooding: localised flooding brought on by poor drainage (Kadave et al., 2016; MCGM, 2007; NDMA, 2019); flooding brought on by Mithi River overflows where settlements have been established in flood plains (Rao et al., 1991; Sahana et al., 2018; Zope et al., 2015); and flooding brought on by a combination of high tide and river overland flow (Hallegatte et al., 2010, 2013; Mohanty et al., 2020). Localised flooding is basically the outcome of unplanned settlements in drain paths, an inadequate drainage system, and reduced drain capacity from waterlogging (Blazkova & Beven, 1997; Kadave et al., 2016; Young et al., 2011). The flood threat has been impacted and made worse by the city's land use strategies, solid waste management procedures, and drainage upkeep (Gupta, 2007; Kulkarni, 2014a; Reshma & Deepankar, 2015). As a result, the city is quite vulnerable to flooding, which can have negative consequences for settlements, the road system, and the day-to-day lives of the citizens (Bhagat & Gavin, 2013; Bhowmik, 2011). The creation of a map of the flood-vulnerable zones is essential for future planning and construction projects as well as flood hazard management to lessen the effects of floods in the metropolis of Mumbai (Mann et al., 2023; Ranger et al., 2011; Sahana et al., 2018). As per the study of Pemmaraju (2012), vulnerability to floods in the metropolis of Mumbai increases due to several institutional and non-institutional factors. The institutional ones are like a lack of coordination between different civic agencies and discretionary authorities, procedural formalities, and land acquisition obstacles for pumping stations at outfall locations. On the contrary, non-institutional factors such as rapid urbanisation, population growth, and alterations in the natural course of the Mithi River due to various anthropogenic as well as socio-economic factors have contributed to

the problem of floods in the metropolis. In accordance with the findings of the climate action plan (2022), Mumbai faces twin challenges: urban flooding and rising heat. Mumbai experiences significant amounts of humidity, which is followed by muggy heat. The evaluation of vulnerabilities and resilience capabilities to different disasters is difficult because the city faces a number of short-duration heavy rainfall events in the monsoon months, which result in an increase in coastal threats brought on by storm surge, coastal inundation, and sea intrusion (Chatterjee, 2010; Kumar et al., 2008; Stecko & Barber, 2007). Furthermore, rapid urbanisation and a lack of proper drainage systems exacerbate the issue of urban flooding (Patankar, 2015; Shukla, 2009; Singh, 2022). In addition, the rising heat poses a threat to public health, especially for vulnerable populations such as the elderly and children (BMC, 2022; Gudhka et al., 2021; Hallegatte et al., 2010). Therefore, it is crucial for Mumbai to prioritise both short-term and long-term solutions in their climate action plan to address these twin challenges (M.Plan, 2009; Patwardhan, 2017; Zimmermann et al., 2023). Apart from that, numerous studies on floods in Mumbai and Navi Mumbai have been conducted in the past, with a major focus on rainfall modelling (Shafapour et al., 2013), urban flood resilience management and planning (Gupta, 2007), vulnerability mapping for disaster estimation (Naghbi et al., 2015; Reshma & Deepankar, 2015), the impacts of urbanisation on flooding (Zope et al., 2015), an integrated flood assessment modelling tool for the coastal urban flood simulation (Kulkarni et al., 2014a), an integrated flood inundation model (Kulkarni et al., 2014b), and the hydrological repercussions of land use and land cover (LULC) change on hazards related to urban floods (Zope et al., 2017). These investigations were conducted independently, without establishing any connection to the underlying mechanisms or variables that are frequently claimed to have an impact on urban flooding.

Geographic information systems (GIS) and remote sensing (RS) technology have recently added a fresh perspective to flood investigations (Farajzadeh, 2002; Masmoudi & Habaieb, 1993). As per the studies of Ali et al. (2019) and Sarkar and Mondal (2020), the study of RS data on the GIS platform produces accurate results for the assessment of flood susceptibility. Several scholars use different statistical methods along with RS and GIS to discover the most plausible,

rational, and reliable result (Hoque et al., 2019; Park et al., 2013; Pourghasemi et al., 2013a). Commonly used statistical techniques are analytical hierarchy process (AHP) (Hammami et al., 2019; Jabbar et al., 2019; Khosravi et al., 2019), weights-of-evidence (Lee et al., 2012a; Porwal et al., 2010; Pourghasemi et al., 2013b), frequency ratio (FR) (Lee et al., 2012b; Naghibi et al., 2015; Regmi et al., 2014), fuzzy logic (Ercanoglu & Gokceoglu, 2002; Ramazi & Amini, 2014; Zou et al., 2013), logistic regression (Al-Juaidi et al., 2018; Jati et al., 2019; Ozdemir & Altural, 2013), artificial neural network (Kia et al., 2012; Wahab & Norasikin, 2018; Zare et al., 2013), decision tree (Nasiri et al., 2019; Shafapour et al., 2013; Yeon et al., 2010), evidential belief function (EBF) (Chowdhuri et al., 2019; Tehrani & Kumar, 2018; Veerappan & Sayed, 2020), adaptive neuro fuzzy inference system (Sahoo et al., 2020; Termeh et al., 2018), and support vector machine (Choubin et al., 2019). As reported in the literature, all of these models were utilised in the vulnerability assessment of any common hazard. MCE techniques based on GIS have been used in a plethora of studies (Afshar et al., 2011; Ahammed et al., 2012; Chung et al., 2011). One of the most widely used techniques for determining criteria weights in MCE is the AHP (Young, 2006), which uses an authoritative pair-wise comparison matrix with its weights. Relying on the AHP, Siddiqui et al. (1996) offered an additive solution to a spatial problem. According to Rao et al. (1991), the process of pair-wise comparisons in AHP is a reasonable one for the establishment of criteria weights. Nevertheless, despite certain unknowns, different researchers have gathered AHP success stories in a variety of sectors (Althwaynee et al., 2014; Feloni et al., 2020; Subbarayan & Sivaranjani, 2020). These studies recognised the AHP model combined with weighted linear combination in GIS as having a strong theoretical foundation (Ghosh et al., 2022; Hasanuzzaman et al., 2022), offering logic for the normalisation of parameters (Chandra et al., 2023), a justification for the expression of decision risk (Fernandez & Lutz, 2010), and a high level of versatility in site adaptability and vulnerability assessment (Hughes, 1986; Mishra & Sinha, 2020; Saaty, 1980). The straightforward and effective practical applications of this technique for determining flood susceptibility have made it widely employed (Korhonen & Lewandowski, 1989; Schmold et al., 2001; Starr &

Zeleny, 1978). The AHP model has been used in the current investigation of mapping flood vulnerability.

When embarking on the above-mentioned research articles, the current investigation thoroughly reviews the published literature pertaining to the topic of urban flood vulnerability in the metropolis of Mumbai. Ramesh and Iqbal (2020) studied the urban flood susceptibility zonation mapping in Mumbai using the evidential belief function, frequency ratio, and fuzzy gamma operator models. They employed 12 parameters in the assessment of flood-susceptible zones. The selection of parameters for assessing flood-vulnerable zones is affected by a combination of different factors like scientific evidence, data availability, research objectives, and stakeholder engagement (De Brito et al., 2018). Parameters such as rainfall, elevation, slope, LULC, soil type, vegetation cover, vicinity to sewers and storm-water drainage, and natural drainage are widely recognised as influential factors in determining flood vulnerability (Taromideh et al., 2022). The current research mainly deals with only seven parameters in the investigation of flood-vulnerable zones and leaves out the important ones, yet the selection of all seven most influential parameters is done on the basis of their importance or effect on the occurrence of floods in the study area. The precision of the demarcation of flood-vulnerable zones is affected by the sensitivity of the parameters used (Ouma & Tateishi, 2014). Elevation thresholds might be too high or too low depending on variables including the terrain of the area, the dynamics of flooding, and the scope of the investigation. In contrast, the vicinity to sewers and storm-water drainage, and natural drainage might vary based on the characteristics of the floodplain, the capacity of the channel, the frequency of floods, and the possibility of riverine or coastal flooding. Slope can enable faster runoff. Flood vulnerability can also be affected by LULC patterns. Conducting sensitivity analyses, incorporating expert knowledge, and validating results with observed flood events can help identify the most influential parameters and improve the accuracy of flood vulnerability assessments.

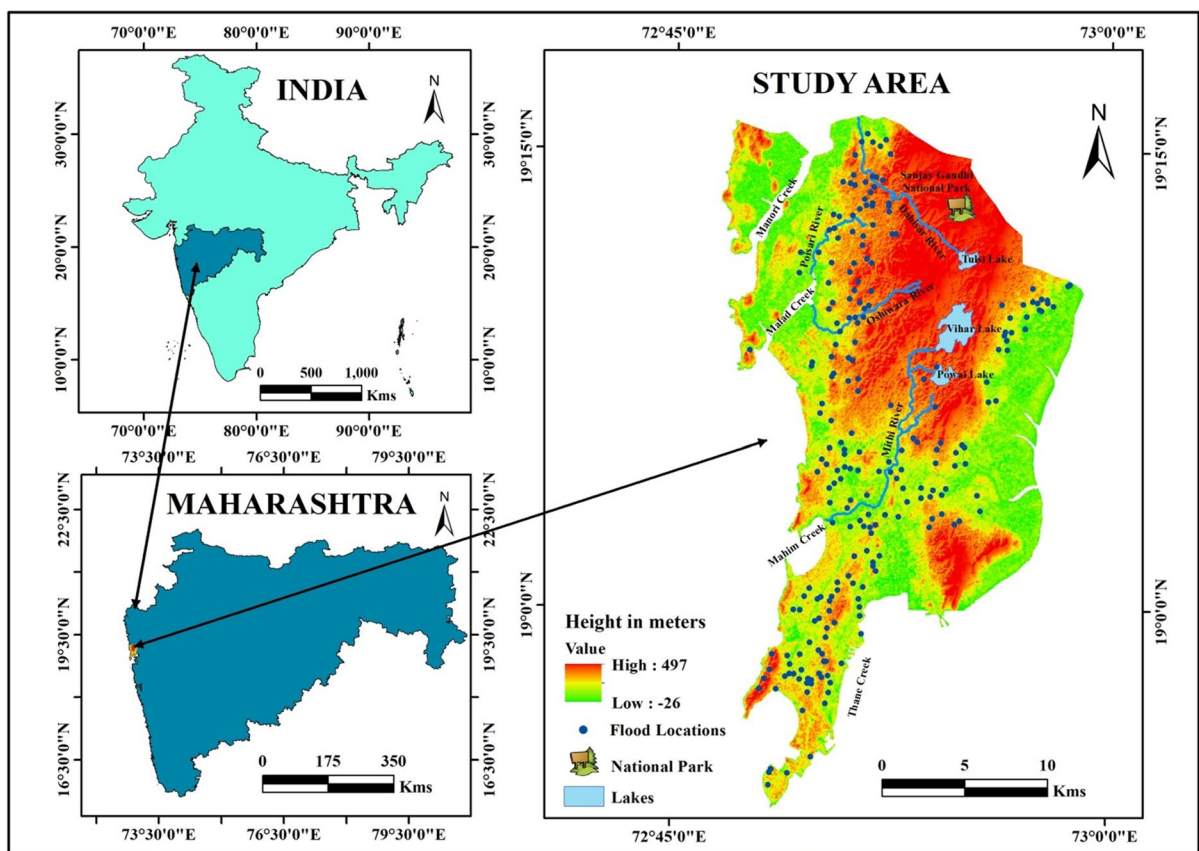
In light of the above-discussed factors, we can take Mumbai as an area of study because the metropolis experiences flood-like situations almost every year due to inadequate drainage system and short-duration heavy rainfall events (Mann & Gupta, 2022; Mann et al., 2023). Apart from that, the demarcation of

flood-vulnerable zones is necessary in order to demarcate flood-prone areas that should be avoided in future development planning. With the aforementioned theoretical framework in mind, the current study used MCE in GIS with the incorporation of the AHP criterion and the weighted linear combination method to identify flood-prone locations using some triggering factors like rainfall, slope, LULC, vicinity to sewers and storm water drainage, vicinity to natural drainage, vegetation, and soil. Therefore, the main objective of the current study is to map flood-vulnerable zones and identify ward-wise flood locations in the metropolis of Mumbai using RS and GIS. The flood-vulnerable map was prepared by analysing and integrating all seven parameters in the geospatial database using the AHP technique, and the results were interpreted. This study presents a novel approach to flood vulnerability assessment through the integration of advanced remote sensing and geospatial techniques. The study goes beyond static flood maps, using real-time data

sources such as weather forecasts and rain gauge data to produce dynamic flood vulnerability assessments. This broader perspective allows for a more comprehensive understanding of the spatial distribution of flood risk. The current study adds new dimensions in the existing literature on flood vulnerability assessment and urban resilience. It provides decision-makers with the necessary tools to take preventative actions that minimise flood risk while promoting sustainable and resilient communities.

### Study area

Greater Mumbai, which has a surface area of around 470 sq. km., stretches between latitudes  $18^{\circ}53'47''$  and  $19^{\circ}16'16''$  and longitudes  $72^{\circ}48'30''$  and  $72^{\circ}51'11''$  (Fig. 1). The westernmost coastal region of the Indian state of Maharashtra is generally referred to as Mumbai. With Thane district to the east, Palghar to the



**Fig. 1** Map of the study area

west, and Raigad to the south-west, the city is considered an extreme coastal area and is surrounded by the western branch of the Indian Ocean and the Arabian Sea on three sides. As a result, the city is sometimes considered a miniature peninsula. The city also hosts a significant span of mangroves on its eastern and western coastlines, which seem to be 149 km in length. As an archipelago of islands, Mumbai's relief and terrain consisted of local hills, coastal cliffs, and ridges with marsh land in between; it possessed a total of 22 hills, well before the fast development period, which has left Mumbai with only three hill ranges: the Ghatkopar hills in the northern part, the Trombay hills in the south-east, as well as the highest Powai hills in the north around Borivali or Sanjay Gandhi National Park. All of these hilly locations mostly encroach on the foothills, and degradation keeps seeping inside.

The Mithi River, which rises near Vihar Lake in the north and rushes southward to reach the Arabian Sea, making an estuary along Mahim Creek, is one of two major rivers that drain the study area. In contrast, the Oshiwara River begins in the Powai Hills and flows northwest to Manori Creek. In addition to this, the highlands have a lot of smaller streams. These rivers have been transformed into sewers filled with tonnes of solid waste due to hasty and quick urban expansion. Usually, the climate of the study area is tropical, with two distinct seasons—wet and dry—as well as places with high to extremely high rainfall. The seasons are marked by moderate heat and high levels of humidity. Due to its tropical climate, the average annual temperature of Mumbai is 27.2 °C. As per IMD, Mumbai, the study area experiences 242.2 cm of annual rainfall. The metropolis of Mumbai has the seventh-highest population in the world. To facilitate administrative convenience, the entire region of Mumbai and Mumbai suburbs has been divided into wards. These wards are labelled A, B, C, etc. in alphabetical order. Mumbai district includes the wards from A to G/South, and Mumbai suburban district includes the wards from H/West to T.

## Database and methodology

### Database

The current analysis uses hourly rainfall data (1985–2020) for two stations, i.e., Colaba and Santacruz, set up by IMD. After the heavy storm event

on July 26, 2005, the Disaster Department of the Municipal Corporation of Greater Mumbai (MCGM) established a dense network of rain gauge stations (60 stations at present) to better assess the spatial distribution of rainfall. The current study uses data that was collected from MCGM and chooses a total of 23 stations (2006–2020) out of 60 (Mann et al., 2023). The stations are selected by using the distance matrix tool in ARC GIS 10.9. The current study is also supported by other types of secondary data that are generated using RS and GIS technology. The specification of all the datasets that are used in the current study is shown in Table 1.

### Methodology

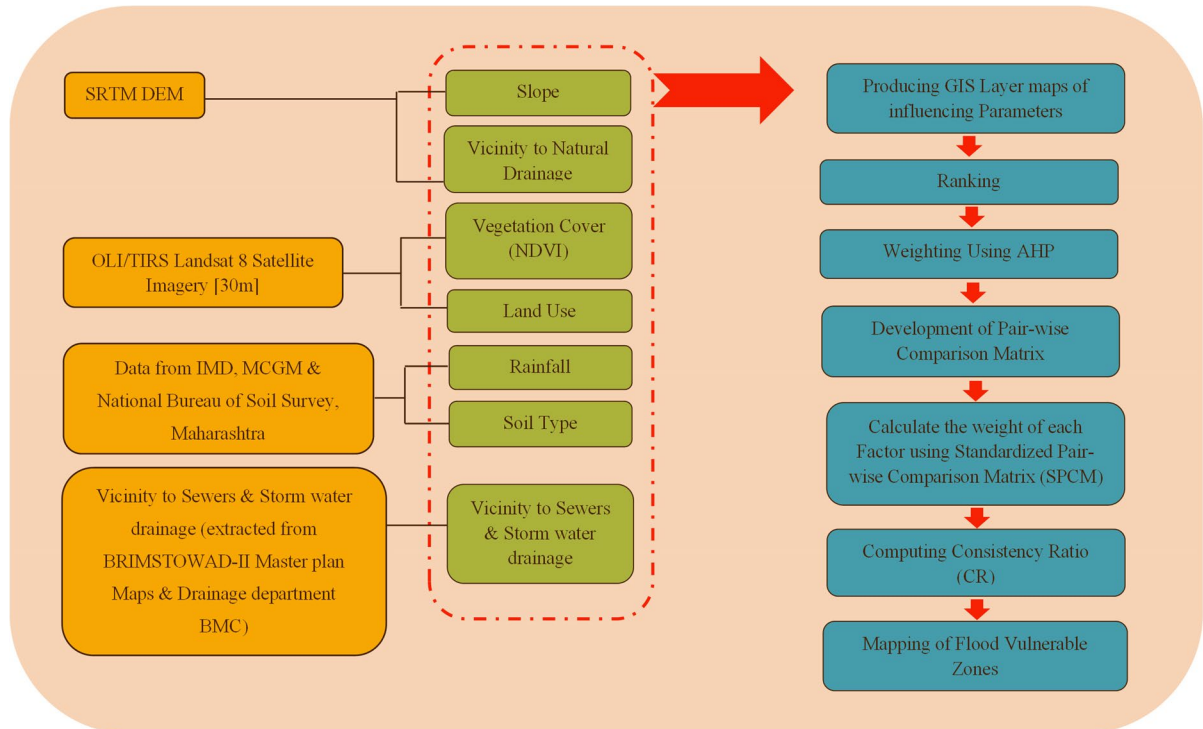
#### *Producing maps of flood influencing factors*

The current study uses the AHP technique in the assessment of flood vulnerability in the study area as it is one of the most convenient methodologies for assessing vulnerability to different disasters. AHP is the best option because it can take into account the relative importance of different elements. It provides a simple decision-making process that helps the decision-maker generate valid inferences (Starr & Zeleny, 1978). Figure 2 graphically depicts the methodology that is used in the present analysis. There are a lot of natural and anthropogenic parameters that affect the course of flooding in the study area. Based on the available literature, we can select the seven most influential parameters that can affect floods in the study area. For each component, GIS maps are initially constructed using a standard georeferencing approach. Rainfall and soil maps were prepared from the data obtained from MCGM, IMD, and the National Bureau of Soil Survey, Maharashtra. By using the surface-slope tool in ArcGIS, the slope in percentage for the study area was retrieved from the computed SRTM, DEM, and SOI OSM sheet, which was later modified using high-resolution satellite images and again used to digitise the map of natural drainage. The Euclidean distance measure in ARC-GIS was used to calculate the vicinity for a distance equivalent to 1000 m for natural drainage.

The vegetation map is produced using Landsat 8 imagery for the year 2020, and the normalised difference vegetation index (NDVI) is performed using Erdas Imagine 2010 software as

**Table 1** Descriptive details of the data collected

Data source	Specifications	Output (flood influencing factor)	Time period
IMD, Pune, and MCGM (Municipal Corporation of Greater Mumbai)	Hourly data	Rainfall	1985–2020, 2006–2020
SRTM (shuttle radar topography mission) DEM (digital elevation model)	Spatial resolution: 30 m	Slope	2020
Satellite image Landsat 8	OLI/TIRS, Spatial resolution: 30mt	Land use land cover (LULC)	2020
BRIMSTOWAD-II (Brihanmumbai Storm Water Disposal System) Draft Master Plan Maps of Storm water Drainage and Sewers	Scale—1:50,000 Year—2014	Vicinity to sewers and storm water drainage	2014
Survey of India OSM Sheet, SRTM DEM	Number—E43A/16(47A/16) Scale—1:50,000 Spatial resolution: 30 m	Vicinity to natural drainage	–
Satellite Image Landsat 8	NDVI; spatial resolution: 30mt	Vegetation	2020
National Bureau of Soil Survey	Maharashtra Scale—1:50,000 Year—1996	Soil	–
Municipal Corporation of Greater Mumbai (MCGM)	Ward-wise flood locations	Map of waterlogging spots	2019

**Fig. 2** Diagram illustrating the adopted methodology for creating the map of flood vulnerability of the study area

$NDVI = (NIR - VIS) / (NIR + VIS)$ . Using Landsat 8 (OLI/TIRS 30 m) multi-spectral data, the map of LULC for the study area was retrieved in ARCGIS software. For LULC classes, supervised classification has been used, which utilises the spectral signatures discovered from the training samples (Sahana et al., 2018). A total of 50 samples were chosen from the image by following the equalised random sampling method (Currit, 2005). Then, the samples are matched with a Google Earth image by identifying the ground features in the ERDAS software. The user's accuracy and the producer's accuracy have been calculated for each class. The overall accuracy of the image is 90% (Supplementary Table 1). The Kappa test is performed to find the degree of accuracy and consistency in a classification that is statistical. Kappa statistics rated the results on a 0–1 scale. It is interpreted by following the guidelines of Landis and Koch (1977). The statistic is rated as (1) 0.01–0.20 insignificant, (2) 0.21–0.40 fair, (3) 0.41–0.60 reasonable, (4) 0.61–0.80 considerable, and (5) 0.81–1.00 nearly perfect or accurate. The accuracy of the classified image is provided by the Kappa statistical index of agreement (KIA), and the result is estimated to be 0.87 (Supplementary Table 1). The accuracy value is considered to be extremely good. Finally, the maps of sewers and storm water drainage from the BRIMSTOWAD-II Draft Plan were used to retrieve the map of artificial drainage. It is a component of the storm water drains project being undertaken in 2014 by the office of storm water drains under the department of disaster management, MCGM. Using the Euclidean distance measure, the vicinity of a distance equivalent to 500 m was calculated (Ramesh & Iqbal, 2020). All maps are transformed to a grid-based integer raster format with the same pixel size of 30 m for each parameter. At last, all the maps were overlaid to produce a combined map of flood-vulnerable zones. Also, a ward-wise map of 234 flood locations is prepared from the data gathered from MCGM and then manually assessed for the relative importance of each parameter against the flood locations. MCA is used to create and combine spatial data for the characterisation of the causative aspects in order to determine the vulnerability of flooding (Feloni et al., 2020). In the GIS context, the weighted linear combination (WLC) approach was employed to implement the AHP pairwise comparison method.

The effectiveness of the AHP model in this study is much better than the conventional methods, showing that the proposed model's performance is excellent for solving the prevalent problems. With such features being one of the few strengths of AHP, it is able to address intricate, multiplex problems with remarkable exactitude and sophistication, surpassing traditional approaches.

#### *Description and order of influencing parameters*

Each aspect that is taken into account is ranked according to the preferences of the decision-makers. Each component is rated according to its expected significance and influence on floods in order to establish criteria scores for each sub-class category. These factors received an inverted ranking. Each sub-class is ranked 1–5 in decreasing order of impact based on reviewed literature and knowledge, where 5 represents high vulnerability to floods and 1 represents low vulnerability. Table 2 displays the grading scheme. The current study makes the assumption that the areas that are most susceptible to flooding depend on a variety of variables, including slope, amount of rainfall, vegetation, soil types, LULC practices, and a natural and artificial drainage network. As a result, depending on these variables, floods can vary considerably over time and location. The following seven parameters were used in the current study, and each of them is shown and saved in a distinct map with the order of their sub-categories shown in Fig. 3 and Table 2.

#### Rainfall

Rainfall is the primary hydrological component that is most frequently employed in studies of floods. Rainfall is the term used to describe the dispersion of liquid droplets over space and time, which regulates surface runoff (Goswami et al., 2006). Since areas with higher rainfall than the annual average are more likely to experience flooding, high rainfall amounts are a marker of substantial flood susceptibility. The map of normal annual rainfall or average annual rainfall is prepared over the years (1985–2020) for all the stations under consideration. As a result, a category weight of 5 is allocated to the heavy rainfall zone, and

**Table 2** Ranking of flood parameters and their sub-categories

Vulnerability parameters	Sub-category of parameters	Ranking
1. Rainfall	> 2300.01	5
	2200.01–2300	4
	2100.01–2200	3
	2000.01–2100	2
	< 2000	1
2. Slope	Very gentle (below 5)	5
	Gentle (5.01–10.00)	4
	Moderate (10.01–15.00)	3
	Steep (15.01–20.00)	2
	Very steep (20.01 and above)	1
3. LULC	Built-up area	5
	Open land	4
	Cultivated land	3
	Vegetation cover	2
	Water body	1
4. Vicinity to sewers and storm water drainage	0–125 mt	5
	125–250 mt	4
	250–375 mt	3
	375–500 mt	2
	> 500mt	1
5. Vicinity to natural drainage	0–250 mt	5
	250–500 mt	4
	500–750 mt	3
	750–1000 mt	2
	> 1000 mt	1
6. Vegetation	Lowest dense vegetation cover	5
	Lower dense vegetation cover	4
	Dense vegetation cover	3
	Higher dense vegetation cover	2
	Highest dense vegetation cover	1
7. Soil	Settlement coastal alluvium	5
	Mud marsh	4
	Vertic Halaquepts	3
	Vertic Ustrepts	2
	Typic Ustorthents	1

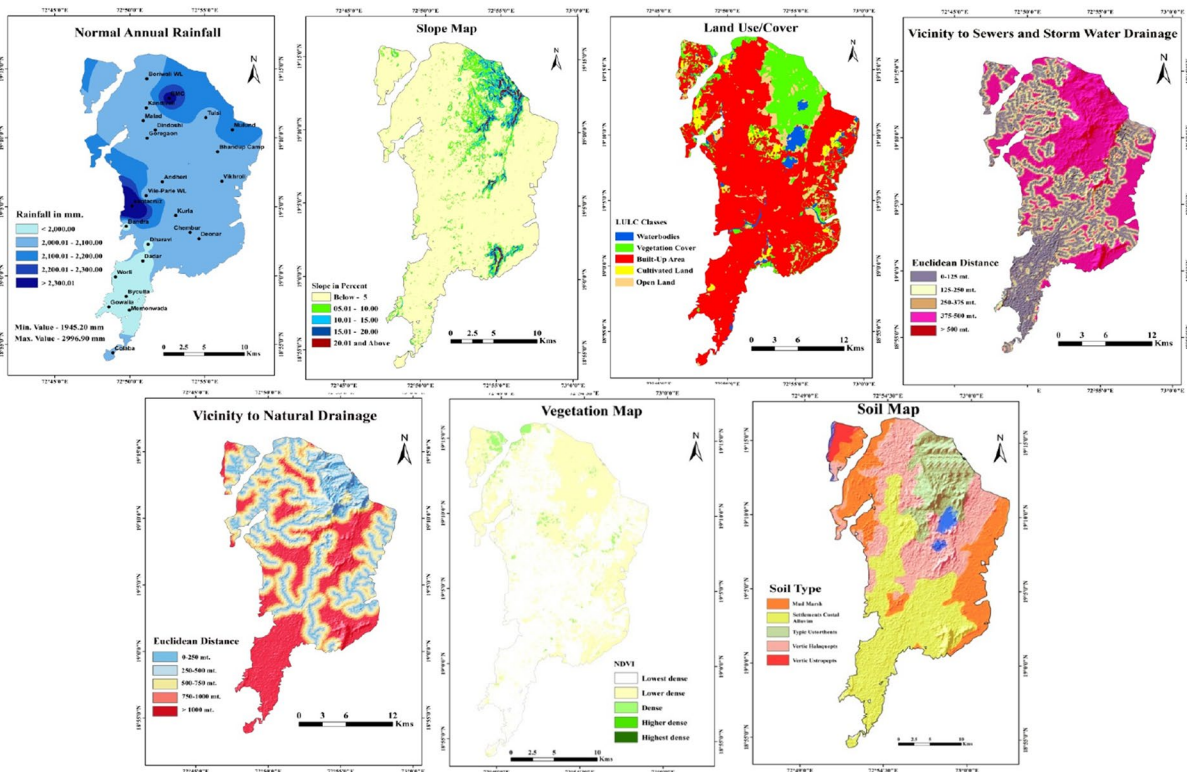
a category weight of 1 is allocated to the relatively low rainfall zone (Table 2).

### Slope

The slope is the most important aspect of hydrology since it directly affects surface runoff and floods. Since sites of low elevation often have a gentle or level slope, they are more susceptible to flooding and

waterlogging because steep slopes generate a huge velocity of runoff compared to flat or gentle slopes and dispose of storm runoff more quickly (Altaf et al., 2013). Runoff from level or gently sloping land is accumulated and released gradually over time (Tehrany & Kumar, 2018). In contrast to high-gradient slopes, low-gradient slopes are even more susceptible to flooding. Historically, the study area was an archipelago of seven islands that had been reclaimed and





**Fig. 3** Maps of flood influencing parameters

established as a land of concrete slabs over a span of five centuries. Additionally, the steeper slope was exploited to provide flat homes for a large number of migrants. As a result, places with very gentle slopes were assigned a class rating of 5, whereas locations with high relief were given a lower ranking, i.e., 1 (Table 2).

**LULC**

Recognising the activities taking place in a location and the various categories of LULC being impacted by recurrent floods is crucial for vulnerability mapping. Due to their significant use of impermeable surfaces, urban areas are impacted by stormwater runoff (Fernandez & Lutz, 2010). Built-up areas dominate the LULC category in the study area. Slums, or nucleated communities, are the main components of densely built-up areas, which are primarily found in the city’s central and southern parts. Evidently, areas with densely built-up space are at greater risk of flooding than areas with less built-up land cover.

Therefore, rankings are allocated as shown in Table 2 based on the kind of land use and its susceptibility to flooding.

**Vicinity to sewers and storm water drainage**

With growing pollution and a lack of concern for it, the sewerage system has emerged as a crucial component and responsibility of the city administration. Sewers are man-made drains that are used to move sewage from homes to disposal sites. Storm water drains (SWDs) are specialised man-made drains that assist in moving and draining extra storm runoff from the city to the countryside and thus minimise floods. The waterlogging in most parts of a megacity like Mumbai is caused by the overflow from these drains, which are primarily ineffective at holding or draining water; therefore, it is crucial to take this into account while analyzing the vulnerability of flooding. The spatial data for these were taken from the BRIMSTOWAD-II Draft Master Plan Maps of Storm Water Drainage and Sewers created in 2014 as part of

the continuing project Storm Water Drains Widening by the Storm Water Drains Planning Cell, a subordinate department of the Disaster Management Cell, MCGM. Using the Euclidean distance tool, the vicinity for a distance up to 500 m was calculated, and it was then classified into 5 classes. The ranks were assigned as per the closeness of location with reference to drainage pipes; i.e., a rank of 5 is assigned to the category of 0–125 m and 1 is assigned to the category of > 500 m (Table 2).

#### Vicinity to natural drainage

The intensity of flooding was thought to be impacted by vicinity to the natural drainage system, implying that the area around some stream or river is quite vulnerable to floods. Here, all streams and rivers are considered to be a part of natural drainage. Furthermore, all the rivers and streams in the study area were digitally captured using the SOI OSM sheet, which was then updated using high-quality satellite images. Using the Euclidean distance tool, the vicinity for a distance of up to 1000 m (1 km) was calculated and grouped into 5 classes. The ranking is given as per the closeness of location with reference to natural drainage; i.e., a rank of 5 is allocated to the category of 0–250 m and 1 is allocated to the category of > 1000 m (Table 2).

#### Vegetation cover

Vegetation cover is the parameter that has the most significant impact on flood vulnerability. Flood susceptibility may increase as vegetation cover declines. This connection is the basis for the widespread inclusion of tree cover and land use in studies of flood susceptibility (Young et al., 2009). Insufficient tree cover under barren or open land makes the area highly vulnerable to flooding; a maximum class weight of 5 is allocated to it, with subsequent classes receiving less weight in the sequence of increasing the area under tree cover (Table 2).

#### Soil type

Since soil properties, particularly those that are more likely to erode, are more vulnerable to floods because the rate of permeability depends on the soil characteristics of a region. Therefore, soil type was chosen as an

influencing parameter (Chung et al., 2011). According to Ross et al. (2018), the soil type of Mumbai falls under the moderately high and high run-off potential groups. The study area has two major soil types, viz., vertic halaquepts and coastal alluvium (soil group Inceptisols). These soils are very fine, slightly deep, poorly drained, and moderately salinised. They are located on very gently sloping areas in residual hills. These soils generally equate to black and laterite in the context of Indian soil classification (Pal, 2013). Therefore, a ranking is assigned as per the soil characteristics against its erosive capacity. The ranking scheme is shown in Table 2.

The above-discussed parameters affect the floods in their own way. The aforementioned presumptions take into account the known correlations between these variables and their impact on flood vulnerability. Researchers can gain a thorough understanding of the regions most vulnerable to flooding and make wise decisions regarding flood mitigation strategies, land management techniques, and urban planning by recognising and incorporating these parameters in the study.

#### *Application of AHP to evaluate the parameters' weight*

Determining the weights for influential flood parameters is a complex problem that involves different criterion functions. If such a scenario is not handled with a reasonable and well-processed methodology, it often results in a miscalculation of the facts. The MCE technique has the potential to logically resolve this matter based on multiple criteria. The AHP technique that Saaty devised was applied in the current investigation (Saaty, 1977). With the use of a preference matrix, in which all recognised relevant criteria are contrasted against one another with replicable preference parameters, AHP is a very well-known and widely used statistical method to determine the necessary weights of each parameter. A pair-wise evaluation matrix, a measure to represent the proportional priority among the components, examines all parameters that are thought to be essential for a decision against one another. As a result, each parameter needs to be given a quantitative score conveying the relative importance of one variable compared to another. A scale for comparison with scores ranging from 1 to 9, which represent the intensity of importance,

was proposed by Saaty and Vargas (1991). Since it has been recognised through psychological studies, a person cannot compare more than  $7 \pm 2$  variables at once. One represents “equal importance”, whereas nine represent variables that are “extremely important” in comparison to other criteria (Supplementary Table 2).

Construction of a pair-wise comparison matrix

A pair-wise comparison matrix of order 7 is shown in Supplementary Table 3 and compares seven parameters (C1, C2, C3, C4, C5, C6, and C7). When parameter C1 and parameter C2 are directly compared, parameter C1 is seen as having equal to moderate relevance, and the remaining parameter is given the same relative weight. The reciprocal of 1/4, or 0.25, is immediately applied to the transposed position.

Standardised pair-wise comparison matrix

The stated preference scores are combined in the following phase to arrive at a quantitative score that represents the weights of the parameters. As a result, eigen scores and vectors of the square preference matrix, which disclose key information about patterns in the data matrix, are computed. Seven eigen scores are provided by the square matrix of order seven mentioned below, which can be used to calculate seven eigen vectors, each of which has seven vector components. Since this eigen vector provides enough information to show by its eigen vector components—the relative emphases of the parameters being investigated—it is viewed as adequate to compute only its eigen vector derived from the biggest eigen score (Bohra et al., 2006). The pair-wise matrix is standardised, and the parameter weights are represented by the standardised matrix’s eigen scores, which are produced as shown in Table 3.

Computing consistency ratio

To evaluate how reliable the assessments have been in comparison to sizable samples of merely random assessments, the consistency ratio (CR) is determined at this point. The AHP always permits a certain degree of consistency, but it should not go beyond a certain point. The consistency ratio (CR), which evaluates the level of consistency, is determined using the random inconsistency index (RI) (Supplementary Table 4),

Table 3 Standardised pair-wise matrix

Parameters	Rainfall	Slope	LULC	Vicinity to storm water drainage	Vicinity to natural drainage	Vegetation	Soil	Total	Priority vector	Weight (%)
Rainfall	C1	C2	C3	C4	C5	C6	C7	2.06	0.29	29.42
Slope	0.33	0.41	0.31	0.34	0.27	0.20	0.19	1.47	0.21	20.96
LULC	0.17	0.21	0.31	0.23	0.21	0.20	0.15	1.23	0.18	17.52
Vicinity to storm water drainage	0.17	0.10	0.16	0.23	0.14	0.25	0.19	0.98	0.14	13.99
Vicinity to natural drainage	0.11	0.10	0.08	0.11	0.27	0.15	0.15	0.63	0.09	8.97
Vegetation	0.08	0.07	0.08	0.03	0.07	0.15	0.15	0.39	0.06	5.58
Soil	0.08	0.05	0.03	0.04	0.02	0.05	0.12	0.25	0.04	3.56
Total	0.07	0.05	0.03	0.03	0.02	0.02	0.04	7.00	1.00	100.00
	1.00	1.00	1.00	1.00	1.00	1.00	1.00			

created by Saaty (1980). If the CR is substantially greater than 0.1, assessments are unreliable because they are too close to randomness. If the CR value is less than or equivalent to 0.1, the inconsistency is acceptable, or else the pair-wise comparison may be altered (Saaty, 1980). The weights are therefore acceptable.

$$CR = \frac{CI}{RI} \tag{1}$$

where  $CI = \frac{\lambda_{max} - n}{n - 1}$ ,  $RI$  is the random consistency index,  $\lambda_{max}$  priority vector multiplies each column summation, and  $n$  is the number of criterion.

$$\lambda = 51.92/7 = 7.42,$$

$$n \text{ (number of criteria)} = 7,$$

$$CI = \lambda - n/n - 1 = 0.07,$$

$$RI = 1.32,$$

$$\text{Consistency Ratio (CR)} = 0.053$$

A consistency analysis is carried out, and the result of  $CR=0.053$  lies below the predefined threshold of 0.1, indicating a high degree of consistency (Table 4). As a result, the weights are acceptable.

### Results and discussion

The authors carefully constructed a spatial database consisting of terrain elevations, LULC classification, precipitation data, soil type, vicinity to sewers and

storm water drainage and natural drainage, and historical flood records as the base components for our analysis. Integration of many datasets is one of the key parts of our modelling framework. Enhancing the accuracy of our flood vulnerability assessment has been achieved through the implementation of the AHP as the main decision-making approach. The validation and calibration of the model against historical flood data verify the accuracy and reliability of its predictions for regions vulnerable to floods. The weighted indices in AHP allowed for a complete evaluation of the factors that contribute to flood risk. The use of historical flood records, together with the overlying of different parameters under different climate conditions, means that the tool provides a prognostic approach for assessing vulnerability levels.

#### Relationship between flood-triggering parameters and flood locations

The causal relationships between flood occurrences and each contributing parameter were investigated. Table 5 depicts the flood-triggering parameters and flood locations in different sub-categories. The majority of flood locations are associated with the “2000–2100” rainfall range, followed by “<2000” (85 flood locations) and “2100–2200” (46 flood locations). The rainfall ranges “2200–2300” and “> 2300” represent the lowest flood locations, with 7, and 4, respectively. Also, it is worth mentioning that none of the stations in the study area experience rainfall less than 1945 mm per year which means that the category <2000 mm refers to rainfall between 1945 and 2000 mm. The locations along the western coastline

**Table 4** Computing the consistency ratio (CR)

Parameters	C1	C2	C3	C4	C5	C6	C7	Criteria weight	Criteria weight	Consistency vector	
Rainfall	C1	1	2	2	3	4	4	5	0.29	2.24	7.63
Slope	C2	0.50	1	2	2	3	4	4	0.21	1.62	7.74
LULC	C3	0.50	0.5	1	2	2	5	5	0.18	1.34	7.67
Vicinity to sewers and storm water drainage	C4	0.33	0.50	0.50	1	4	3	4	0.14	1.10	7.85
Vicinity to natural drainage	C5	0.25	0.33	0.50	0.25	1	3	4	0.09	0.61	6.75
Vegetation	C6	0.25	0.25	0.20	0.33	0.33	1	3	0.06	0.39	7.04
Soil	C7	0.20	0.25	0.20	0.25	0.25	0.33	1	0.04	0.26	7.24
Total		1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00		51.92

**Table 5** Relationship between flood-triggering parameters and flood locations

Flood vulnerability parameters	Sub-category					Total
Rainfall	<2000	2000.01–2100	2100.01–2200	2200.01–2300	> 2300.01	
Flood Locations	85	92	46	7	4	234
Slope	Very steep [20.01 and above]	Steep [15.01–20.00]	Moderate [10.01–15.00]	Gentle [5.01–10.00]	Very gentle [below 5]	
Flood locations	0	0	23	48	163	234
LULC	Water body	Vegetation cover	Cultivated land	Open land	Built-up area	
Flood locations	3	5	8	11	207	234
Vicinity to sewers and storm water drainage	> 500mt	375–500 mt	250–375 mt	125–250 mt	0–125 mt	
Flood locations	5	14	30	38	147	234
Vicinity to natural drainage	> 1000 mt	750–1000 mt	500–750 mt	250–500 mt	0–250 mt	
Flood locations	135	11	4	19	65	234
Vegetation	Highest dense vegetation cover	Higher dense vegetation cover	Dense vegetation cover	Lower dense vegetation cover	Lowest dense vegetation cover	
Flood locations	0	2	19	54	159	234
Soil	Typic ustorthents	Vertic ustrepts	Vertic Halaquepts	Mud marsh	Settlement coastal alluvium	
Flood locations	0	0	67	21	146	234

Compiled by authors

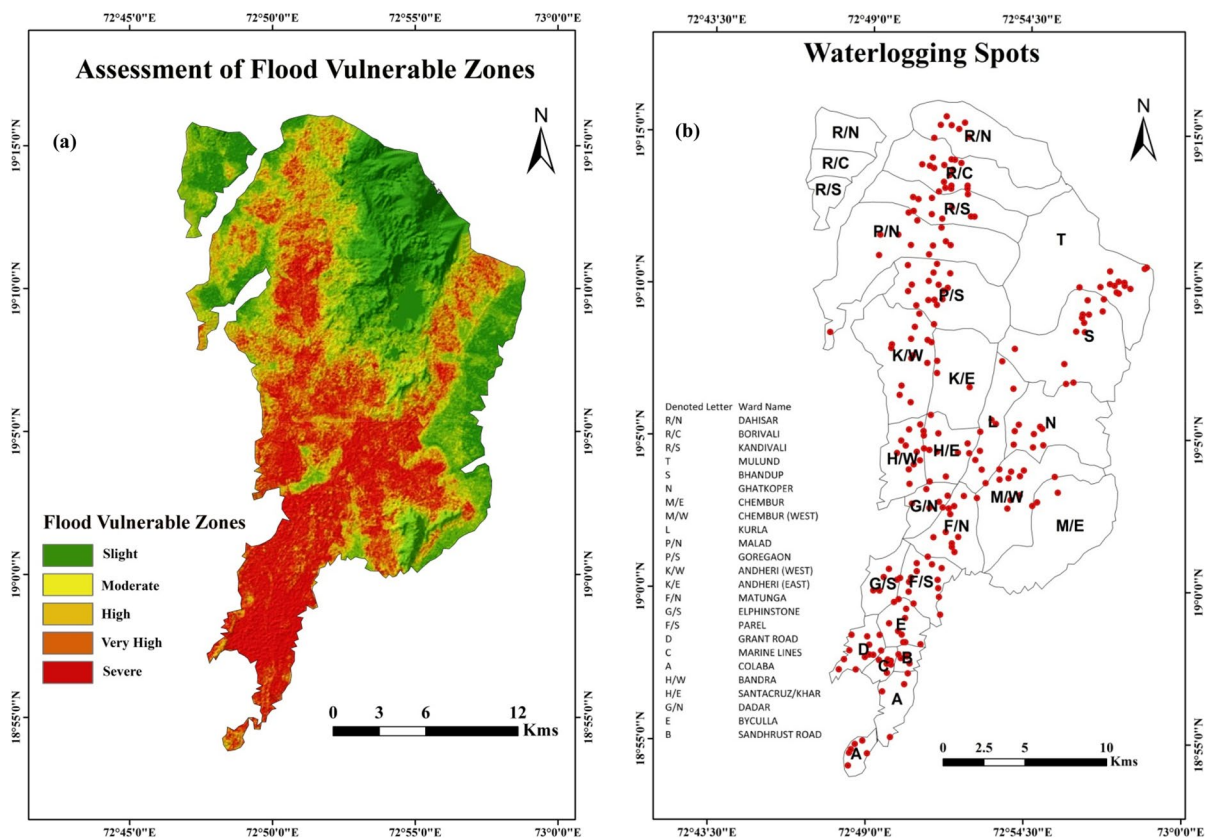
(i.e., Santacruz) have seen 2922.30 mm of average annual rainfall over the past 5 years (2016–2020), with the highest amounts received in the years 2020 (3721.99 mm) and 2019 (3428.22 mm). By combining the spatial patterns of normal annual rainfall and flood locations, it is apparent that 95% (i.e., 223) of flood locations are concentrated in regions where the distribution of rainfall varies between below 2000 to 2200 mm (Fig. 3; 4b). In terms of slope, the highest number of flood locations (163 out of 234) occurs in areas with a “very gentle” slope range, followed by a “gentle” slope range with 48 flood locations. For the “very steep” and “steep” slope ranges, no flood locations have been recorded (Table 5). It is discovered that almost 90% (i.e., 211 out of 234) of flood locations lie in the categories of gentle and very gentle following the spatial analysis of flood locations with the slope conditioning factor, making the slope one of the main flood impacting parameters (Figs. 3; 4b). The “Built-up Area” category has the highest number of flood locations, with 207 out of 234; i.e., around 88.46% of all flood locations are discovered in those areas where the land dominates under the “built up”

category. Other land cover categories such as “water body”, “vegetation cover”, “cultivated land”, and “open land” have comparatively lower numbers of flood locations (Figs. 3; 4b). The sub-category-wise spatial patterns of the flood locations, as indicated by the outcomes, subvert presumptions. Cities tend to have a high degree of susceptibility to floods, given that population density and infrastructure are of the utmost importance. The finding underscores the necessity of multifaceted flood risk management solutions.

There is very little chance of percolation and infiltration due to the compact concretisation. The city has essentially no level of infiltration, as seen by the recurrent annual waterlogging episodes, even from a light rain event (Ramesh & Iqbal, 2020; Zope et al., 2015, 2017). This makes the study area highly vulnerable to floods. The flood spots are dispersed across different proximity ranges, with the highest number of flood locations (147 out of 234) concentrated in areas with a proximity range of “0–125 m”. With only five flood spots, the “> 500 m” proximity range has the lowest number of flood locations (Table 5). Furthermore,

the majority of flood locations (135 out of 234) are in areas with a proximity range of “> 1000 m”. The flood locations in the vicinity of natural drainage indicate that only 27.78%, or 65 flood locations, lie in the 0–250-m category. The flood locations decrease as the vicinity range decreases, with the lowest number of flood locations (4) found in areas with a vicinity range of “500–750 m”. This happens because the city has no natural source of drainage and contains a maximum number of flood locations (Figs. 3, 4b; Table 5). It is clear that the extensive network of artificial drainage systems, natural streams, and different creeks that turned into sewers plays a crucial role in the management of the urban ecosystem in the study area (Bohra et al., 2006). With the increase in water level in these streams owing to heavy rainfall, the nearest settlement gets flooded (Fact Finding Committee (FFC), 2006). The mapping of flood susceptibility revealed a clear relationship between land use and flood risk, with densely populated metropolitan areas and

large quantities of impermeable surfaces exhibiting increased sensitivity because of poor natural drainage and excessive surface runoff (Mishra & Sinha, 2020; Mohanty et al., 2020). The flood locations are spread across different vegetation density categories. Out of the 234 locations, the “Lowest Dense Vegetation Cover” category has the highest number of flood spots (159), followed by Lower Dense Vegetation Cover (54 flood locations). No flood locations are associated with the “Highest dense Vegetation Cover” category (Table 5). In settlement areas where the major soil type is coastal alluvium, flooding occurs more frequently. The soil type is affected by the different types of land use because it affects the erosive capacity of the soil (Borrelli et al., 2020). Therefore, flood vulnerability is likely to rise in areas where the major soil type is coastal alluvium. The highest number of flood locations (146 out of 234) occurs in areas where the dominant soil type is settlement coastal alluvium. Other soil types, such as “Vertic Halaquepts” and “Mud



**Fig. 4** Map of a flood-vulnerable zones (using AHP) and (b) ward-wise waterlogging spots

Marsh”, also contribute to flood vulnerability, but to a lesser extent. Saltpans and marshes are another class of soil type where the frequency of flood occurrences is really high. It occurs because these marshlands were created by digging and cleaning activities along the banks of the Mithi River in the study area, which typically overflows onto these marshlands and the nearby settlements during heavy rainfall events (M. Plan, 2009). The mapping of flood vulnerability revealed that areas with steep slopes, high amounts of rainfall, sparse vegetation cover, impermeable soil types, and urbanised land use practices exhibited the highest levels of vulnerability to flooding. The approach adopted in the current study in the assessment of flood vulnerability effectively identified the most susceptible locations through the integration of several spatial datasets, underlining the need to take into account multiple elements like rainfall, slope, LULC, vicinity to sewers and stormwater drainage, and natural drainage, vegetation, and soil types. It became clear that most of the flood locations with insufficient drainage systems were associated with higher exposure levels when the flood vulnerability map was compared with the existing drainage networks, highlighting the necessity of efficient drainage systems in lowering flood risk. The current research relied on a mapping approach which we needed to assure valid performance through rigorous validation analyses. We did so by matching our resulting vulnerability map with historical records detailing areas prone to flooding caused by previous flood events. Importantly, we found congruent results between these records and our assessment through this methodological framework demonstrating eminent reliability. While our model is quite detailed in its scope, there are still some limitations, one of which is data coverage and quality. It drives an important conversation about how we can better collect data and leverage new technology in order to more accurately assess flood vulnerability.

#### Ward-wise analysis of flood locations

Supplementary Table 5 shows crucial information pertaining to both the Mumbai and Mumbai Suburban districts. This information commands attention as it outlines specific details on ward names, denoted letters, locations, areas, and the number of flood locations present therein. Locations such as CST and Church Gate are part of Colaba Ward (A) in the case

of Mumbai City District, where seven flood locations are detected. Within the boundaries of Sandhurst Road (ward B), spanning across an area of 266 ha, are flood locations such as Sandhurst Road and Masjid, and four spots have the issue of flooding. In terms of size within the city district, Marine Lines (ward C) is the smallest ward, covering an area of 191 ha. There are seven spots where flood occurs in the Marine Lines area. A total of twelve waterlogging spots are recorded around the area of Bombay Central, which is part of Ward D (Grant Road). Additionally, six more such areas exist within Ward E (Byculla). Parel (Ward F/S) has three waterlogging spots around Cotton Green. Matunga (Ward F/N) comprises Mahim and Matunga Road along with seven waterlogging spots, and Ward G/N (Dadar) comprises Wadala and Dadar along with 10 locations that frequently get flooded. Elphinstone Road, Curry Road, Sewri, and Mahalaxmi are part of the ward of G/S (Elphinstone) and include a total of 20 flood locations. Flooding is a significant issue in Mumbai, with 76 flooded spots identified in the Mumbai city district alone. These spots are distributed across different wards, with Elphinstone (G/S) ward having the highest number of 20 flooded locations (Supplementary Table 5).

The suburban area of Ward H/W, which is part of Bandra, includes a total of nine flood locations. In addition, the ward H/E (Khar) found a total of 10 flood locations in and around Khar East and Kherwadi. Ward K/E (Andheri East) encompasses an area of 2400 ha with five flood locations. Jogeshwari and Vileparle fall under Andheri (West) (Ward K/W), and the number of flood locations detected is 12. Goregaon (Ward P/S) includes the Goregaon area and has 17 spots that are prone to floods. In Malad (Ward P/N) and Kandivali (Ward R/S), there are a total of nine flood locations in each ward. In Borivali Ward, there are 21 flood locations, and seven flood locations in the northernmost ward, i.e., Dahisar. Kurla (Ward L) contains 19 flood locations, including Tilak Nagar and Chuna Khatti. The northeastern ward of Chembur (M/E) includes the flooded locations of Mankhurd and Govandi and has only three flood spots, whereas Chembur (West) has just one spot susceptible to flooding. Pantnagar and Vikhroli fall under Ghatkopar (Ward N) and have eight flood locations. There are a total of 16 flood locations in Bhandup (S), and Mulund consists of 12 flood locations. The Mumbai Suburban district also faces flooding issues, with

a total of 158 flooded spots identified in the known wards. Borivali (R/C) ward has the highest number of flooded spots, i.e., 21 (Supplementary Table 5). This indicates that drainage systems and encroachment in low-lying areas are to blame for flood events that have occurred in and around Mumbai city. The majority of the drainage systems in the study area are gummed up with solid waste, making these areas extremely vulnerable to floods. In contrast, the frequency of floods is higher due to the influence of increased runoff in and around urban peripheries. The parameters taken in the current study are strongly associated with flood vulnerability. This shows that although the main underlying cause of the flood is the intensity of the rainfall, it is not the only crucial parameter affecting the floods in a region like Mumbai. Overall, the data highlights the need for proper urban planning and infrastructure development to address the flood issues in Mumbai and Mumbai Suburban districts, particularly in those wards with a higher number of flood locations. Disseminating this type of data can provide valuable insight about potential issues that residents or organisations might encounter during bouts of heavy rainfall. According to the findings, the AHP model offers great potential for revealing detailed insights on flood vulnerability factors. We found that changes in factor exposures caused subtle differences in risk quantification, which emphasises the need for sound sensitivity analysis.

### Vulnerability analysis

Based on the AHP technique, weights are computed in percent as 29.42, 20.96, 17.52, 13.99, 8.97, 5.58, and 3.56 for rainfall, slope, LULC, vicinity to sewers and storm water drainage, vicinity to natural drainage, vegetation, and soil type of the study area, and consistency ratio (CR) is computed as 0.053. This

demonstrated a respectable level of accuracy in the pair-wise comparison matrix. Using the arithmetic weighted sum overlay technique in the Arc GIS 10.9 software, each parameter's raster layer in grid format is multiplied by its assigned weight prior to being added together. Small values denote low vulnerability to floods, and high values denote high vulnerability to floods. The composite values are generated in the range of 144 to 384. The merged map is reclassified into five categories—severe, very high, high, medium, and slight (Fig. 4a)—using the quantitative method of standard deviation (SD) (Table 6). In the study area, the flood-vulnerable area is computed as follows: 46.72% (severe), 11.91% (very high), 6.83% (high), 5.39% (moderate), and 29.15% (slight) (Table 6). Most of the waterlogged spots, i.e., 85.46%, were found in areas that fall under the category of severe to very high vulnerability, and only 14% of locations fall in the other three categories as per the data of the flood locations that are collected from the MCGM authorities. According to the findings of the study, which are based on a combined weighted analysis of all parameters, the north and north-eastern parts of the study area lie in a slight to moderately vulnerable zone, whereas the south and south-western parts of the study area come under the category of a severe to very high vulnerability zone.

In light of the above discussion, achieving effective urban flood control initiatives hinges on conducting an initial vulnerability analysis phase first and foremost; it allows us to better understand complex parameters that contribute towards flood vulnerabilities in any given city or region by identifying key areas at risk. With comprehensive data collection supported by community engagement initiatives, we have access to even more insights into entrenched parameters that exacerbate existing vulnerabilities, adding new options for mitigation tactics that can include

**Table 6** Area under flood vulnerability using AHP

Sr. no	Flood-vulnerable zones	Area (sq. km)	Area (%)	No. of waterlogged locations	% of waterlogged locations under flood vulnerable zone
1	Slight	127.59	29.15	5	2.14
2	Moderate	23.59	5.39	7	2.99
3	High	29.90	6.83	22	9.40
4	Very High	52.13	11.91	70	29.91
5	Severe	204.50	46.72	130	55.55
Total		437.71	100	234	100



everything from enhancing existing infrastructure to creating early warning systems, all aimed at providing robust emergency response plans when necessary. Prioritising such actions creates layers of resilience even amidst difficult environmental conditions, ultimately leading to the safeguarding of both lives and property for years to come.

## Discussion

Although the current research is explicitly conducted for the city of Mumbai, the present study also makes generalisations about different coastal cities in India and in other parts of the world. The study area has traditionally experienced significant urbanisation as a result of different aspects linked with colonial expansion, economic growth, and a rising population (Bhagat & Gavin, 2013; Bhowmik, 2011). In the case of India, LPG reforms led to substantial growth in urban planning for most of the megacities between the 1990s and 2000s (Ravan, 2014). Since flood risk diagnostic techniques were not as sophisticated and accurate as they are now, it caused uncontrolled growth and encroachment in flood-prone areas. In this regard, we find ourselves in a situation where a significant portion of city planning for the future has already been approved. Another significant problem in the majority of Indian cities is the delay in development projects. Furthermore, we now know more about the likelihood of flooding in cities from a geographical perspective, and there are a lot of recent buildings and structures that have been built in flood-prone locations. As a result of climate change, heavy rainstorms are becoming more frequent and intense in different parts of India (Goswami et al., 2006; Guhathakurta & Rajeevan, 2008; Rakhecha & Pisharoty, 1996). Due to the occurrence of these heavy storm events, national authorities will need to re-evaluate the return periods of different durations in order to better assess the risk of flooding in different megacities on a regular basis (Zope et al., 2015). The urban development plan of the city identifies some built-up locations as being at risk of flooding. The presence of these locations in vulnerable areas makes this sensitive position even more complicated. Government agencies must deal with this challenging scenario because landowners have already secured their rights to construct in these areas. Local authorities have to decide between suing those property owners in court and forcing them to pay significant

private expenditures on flood mitigation facilities in order to approve the execution of development plans. These investments can also be politically divisive in some situations because of their high socio-economic profitability.

A number of different megacities in India are experiencing this intricate confluence of events (like heavy storm events), and it will occur more frequently over the next few decades (Mann et al., 2023; Rajeevan et al., 2008). In this regard, the MCE approach, in association with the AHP technique, is used in the analysis of flood-influencing parameters. It has added new insights into the vulnerability assessment of any common hazard in a city like Mumbai that may be extremely helpful in identifying future incidents. We were able to see how different parameters used in the current study significantly increased the vulnerability of the city of Mumbai to floods using the AHP technique. The study area originally comprised seven islands: Bombay, Mazagaon, Parel, Worli, Mahim, Little Colaba, and Colaba. The Mumbai metropolis was formed by reclaiming all of these islands. The metropolis, which is now bursting with concrete buildings, was formerly a mangrove forest-dominated mixed wetland habitat. However, mangroves have been destroyed over the past century, and streams are now blocked with construction waste, leaving the city without its natural barriers (Sarkar, 2017). The process of rapid urbanisation has contributed to the problem of flooding because it has altered the hydrology, morphology, habitat, and ecology of the study area (Zope et al., 2015). The flood locations across sub-categories of different parameters show interesting results. The slope categories of less than 5 m and 5.01–10 m (211 flood location), the built-up land category (207 flood location) in LULC, the vicinity of sewers and storm water drainage of less than 125 m (147 flood location), the category of natural drainage of <250 m (65 flood location), the rainfall category of below 2000 to 2200 mm (223 flood location), the category of lowest dense vegetation (159 flood location), and the category of coastal alluvium (146 flood location) in soils all exhibit higher interactions with flood locations. In the case of natural drainage, the sub-category of >1000 mt. has 135 flood locations (Table 5). It is because most of the flood locations lie in city district, and the city has no network of natural drainage. Moreover, poor drainage, Mithi River overflow, and a combination of river overflow and high tides all contribute to the frequent floods in Mumbai (M.Plan, 2009;

Kadave et al., 2016; Mohanty, et al., 2020). Also, the analysis of ward-wise flood locations reveals interesting insights. Elphinstone-ward (20 flood locations) in the city district and Borivali-ward (21 flood locations) in the sub-urban district have the highest number of flood locations. On the contrary, Parel ward in the city district and Chembur (west) in the sub-urban district have the lowest number of flood locations (Supplementary Table 5). The flood preparedness guidelines (NDMA, 2019) emphasise how crucial it is to preserve the natural processes that control flood water. The ecological setting of the study area naturally protects the city from flooding; however, the rivers of Mumbai, which serve as the natural drainage of the city, are in such bad condition that they are unable to perform their intended purpose. When it rains, one of the main rivers, the Mithi, which is clogged with industrial and domestic waste, overflows (M.Plan, 2009). Similar factors also make the areas along other important rivers, like the Dahisar, Poisar, and Oshiwara rivers, prone to flooding. The wetlands conservation and management guidelines were revised in 2017, and salt pans that serve as buffers against high tide and heavy rainfall were no longer recognised as wetlands (GIWR, 2017).

The weights for different criteria are calculated for the different parameters under consideration. Then, the parameters are classified according to their intensity of importance, i.e., from a severe to a slight category. The results revealed that most of the flood locations (approx. 85%) lie in areas of very high vulnerability. The findings of the study show that the delineation of flood-prone areas marks a major stride towards comprehending the intricate nuances of flood risk. The results of the current study are interesting and informative, but they need deeper investigation to understand them well and draw boundaries. Humans themselves will be directly exposed to the risk of flooding as the natural barriers against climate change are destroyed to make room for the habitat of a burgeoning population. Thus, it may be inferred that there is a risky general trend in the existing urban expansion patterns to emphasize flood risks that occur in the study area, demanding a rethinking of development patterns that put more emphasis on flooding issues. The cities of India are not the only ones that face issues of urban planning and flooding. It is a phenomenon that, with different regional variations, is starting to have an increasing impact in other cities all over the world. Specific problems exist in different metropolitan regions

that have expanded rapidly in developed nations, like Seoul (Choi et al., 2021), or in cities in developing nations, like Rio de Janeiro (Lourenço et al., 2020). In this regard, the methodological framework (AHP technique) suggested can be extremely helpful in detecting some specific problems associated with flood vulnerability by taking into account all seven parameters used in the current study.

The current study confirmed the necessity of incorporating various sources and variables into the flood vulnerability assessment. In this regard, the study employed the AHP, which helped us to order these variables through a step-by-step process of prioritisation and ranking. Yet, considering the fundamental nature of the method presented, it must be understood that it still has a number of limitations. Although the AHP model accounts for these attributes, further work could be conducted as a matter of improving methodology and increasing our understanding of how they play a part in flood vulnerability. Apart from that, the analysis performed must be enhanced by applying it to further case studies to confirm its validity. Given its exploratory nature, the AHP technique might have overlooked different parameters whose inclusion could assist the procedure in becoming more dependable and resilient in other examples with varying threshold constraints. Furthermore, with regard to policy implications, it would be captivating if the technique could assist at the spatial level in a fragmented way instead of an aggregated one, as indicated in the ongoing investigation. It is the need of the hour to develop a more capable graphic design tool with increased computational power that could integrate urban planning and flooding and transmit results in a localised manner for each sector of the city. This would make it possible for what is essentially straightforward scientific research to develop into a real graphic tool to assist in the development of urban planning for cities.

## Conclusion

In this study, urban flood-vulnerable zones in Greater Mumbai, a highly flood-prone metropolis, were delineated using the AHP technique. The slope categories of less than 5 m and 5.01–10 m, the built-up land category in LULC, the vicinity of sewers and storm water drainage of less than 125 m, the category of natural drainage of <250 m, the rainfall category of below

2000 to 2200 mm, the category of lowest dense vegetation, and the category of coastal alluvium in soils all exhibit higher interactions with flood locations. The present study draws the conclusion from the causal relationship of all the parameters that built-up land use and vicinity to artificial sewerage systems are the main influencing parameters for flood vulnerability in the study area, along with a strong association with the natural parameters like rainfall, slope, and soil.

We may comprehend the underlying triggering parameters that are typically neglected in the vagueness of blind infrastructure investment by assessing the flood vulnerability that is conducted in mainstream and academic studies of metropolises like Mumbai, Hyderabad, Bangalore, and Delhi. Megacities are frequently viewed as the sole loci of economic and financial development in developing countries, where environmental changes are made while obnoxiously ignoring the risk of natural disasters. The outcomes of this study, which frequently suffers from administrative problems, indicate that urban expansion, whether planned or unplanned, can significantly alter the hydrological processes of a watershed. In the scenario of Mumbai, this damage has gone beyond reasonable limits, culminating in rivers and streams that have been transformed into city sewers blocked with solid waste. Even a brief period of rainfall causes floods in this metropolis since the land surface has achieved zero levels of infiltration. However, despite the fact that urban land use change is the most essential parameter in the study of flood vulnerability, it simply cannot be chosen in isolation. As a result, another significant conclusion that can be drawn is that in order to understand the full geographic and climatic narrative of urban floods, it is necessary to include all the other parameters (rainfall, slope, vicinity to sewers and storm water drainage and natural drainage, vegetation, and soil) and correlate their relationship with floods.

The critical discussion of the results mentioned in the current study highlights the limitations and difficulties involved in flood risk mapping. The study findings provide important new evidence in this domain, but at the same time, they remind us how much we still have to improve our data, models, and understanding of the complexities around different degrees of flood-prone areas. This study lays the groundwork for further investigations to improve disaster resilience and community welfare in flood-prone areas. The MCGM and the relevant authorities

should therefore repair the current abnormalities in the system, such as the storm water drainage system, with the aid of such scientific investigations carried out at multi-scalar levels in order to minimise the risk of future damage. The following suggestions are made by the authors of the work:

1. Employing low-impact development best management practices (LID-BMPs) for urban surface runoff control. LID-BMPs are green approaches for managing stormwater that help control runoff and maintain pre-development hydrologic characteristics. These practices include the local retention of stormwater using control measures like rain gardens, rain barrel, green roofs, permeable pavement, conservation easements, vegetated/grassed swales, infiltration trenches, and bio-retention systems.
2. Using a multi-objective optimisation decision-making framework: A framework that combines the storm water management model (SWMM) with Non-Dominated Sorting Genetic Algorithm-II (NSGA-II) models can be used to optimise the performance of LID-BMPs in terms of cost-benefit analysis and runoff volume reduction.
3. Optimum selection and placement of LID-BMPs helps hydrologists select and achieve maximum ecological benefits with minimum expenses. LID-BMPs help reduce runoff by 22–26% for the same expenditures.
4. Considering the complexity of the parameters involved, LID-BMPs help in attenuating urban surface runoff at the watershed scale, which in turn further promotes the concept of sponge cities.
5. Identifying flood-prone locations on large-scale maps.
6. Make laws governing construction activities in floodplains and enforce them.
7. Provide specific areas for the flood plain, such as by forestation, land sloping, and the construction of small reservoirs, check dams, and ponds, in order to increase the water holding capacity of a watershed.
8. The potential of the high runoff should be matched while improving the sewers and storm water drainage systems, and two parameters must be taken into account while planning the city structures: the trend in population growth and the changing climate.

9. Demarcate vulnerable zones to halt the ruthless encroachment onto marshlands and other fragile water bodies.
10. To plan for restoration in the form of shelter dwellings both before and after disasters.

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**Data availability** All supporting data are mentioned in Table 1 of the manuscript.

**Data availability** Not applicable.

#### Declarations

All authors have read, understood, and complied as applicable with the statement on “Ethical responsibilities of Authors” as found in the Instructions for Authors.

**Competing interests** The authors declare no competing interests.

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