Research Article

GIS-based flood risk assessment using multi-criteria decision analysis of Shebelle River Basin in southern Somalia

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Abstract

Floods are the most common and expensive natural calamity, affecting every country. Flooding in the Shebelle River Basin (SRB) in southern Somalia has posed a significant challenge to sustainable development. The main goal of this study was to analyze flood hazard, vulnerability and risk in the part of SRB using GIS-based Multi-Criteria Decision Analysis (MCDA). The flood hazard map was constructed using seven important causative factors: elevation, slope, drainage density, distance to river, rainfall, soil and geology. The results demonstrate that very low, low, moderate, high, and very high flood hazard zones correspond to 10.92%, 24.97%, 29.13%, 21.93% and 13.04% of the area of SRB, respectively. The flood vulnerability map was created using five spatial layers: land use/land cover, population density, distance to road, Global man-made impervious surface (GMIS), and Human built-up area settlement extent (HBASE). In addition, the results of the flood susceptibility and vulnerability maps were used to create a flood risk map. The results demonstrate that for the Shebelle River Basin, 27.6%, 30.9%, 23.6%, 12.1%, and 5.7% area correspond to very low, low, moderate, high, and very high flood risk zones, respectively. The Receiver Operating Characteristics-Area Under the Curve (ROC-AUC) of the flood hazard model exhibited a good prediction accuracy of 0.781. The majority of the basin is at risk of flooding in the very low, low, and moderate ranges; however, some tiny areas are at risk of flooding in the high and very high ranges. Flood hazard, vulnerability and risk maps should be provided and distributed the authorities responsible for flood protection so that people are aware flood risk locations.

Article Highlights

- GIS-based analysis identified flood hazard, vulnerability and risk zones in the Shebelle River Basin, Somalia.
- Majority of the basin falls in very low to moderate risk ranges, with small areas at high and very high risk.
- Flood hazard, vulnerability and risk maps can guide flood protection efforts and raise awareness among local populations.

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1 Introduction

Natural hazards have been regarded as one of the most serious concerns confronting both industrialized and developing countries in recent years [1]. Natural disasters are responsible for 40% of all socioeconomic losses worldwide [2]. Floods are, without a doubt, among the most prevalent and destructive natural catastrophes worldwide, notably in Africa. It impacted negatively on both the social and economic fronts, as well as the environment [3–7]. This natural occurrence occurs mostly as a result of global warming, which alters the rate and intensity of rainfall, resulting in extreme rainfalls that cause dams to burst, seas to flood, and streams to overflow [8]. Following that, they generate severe floods in a given area for a specific period of time, resulting in socioeconomic losses, fatalities, and property destruction [9]. Today, various experts from around the world, including hydrologists, hydrogeologists, and planners, are interested in assessing and managing floods. They are seeking an effective and reliable approach to reduce the risk of flooding. Indeed, flood risk management and assessment are essential for reducing risk and ensuring long-term socioeconomic growth [10].

Fluvial floods are the most common and expensive natural calamity, affecting practically every country on the earth [11]. They occur when a river's storage capacity is exceeded, and the excess water overflows the banks and floods the surrounding low-lying lands, resulting in major social, economic, and environmental consequences such as loss of life and negative population consequences, infrastructure and vital services damage, crop and animal damage, disease spread, and water supply pollution [12]. Heavy rainfall at river mouths, ice jams, melting snowpack, and land-use change are all factors that contribute to river flooding (such as deforestation and urbanization) [13]. Runoff from heavy rains causes river flooding, and as urbanization increases, so does impervious area, resulting in increasing runoff rates. Saturated soils, excessive suspended matter, and landslides all contribute to floods.

Flood risk management relies heavily on predicting the size of river floods. There are three common approaches to flood prediction: (i) monitoring storm progress (e.g., quantity of rainfall) can be used to forecast short-term flood events; (ii) assessing the frequency of flooding through statistical analyses allows determining the recurrence interval for any year and for a given discharge in the stream (without explicitly characterizing the flood area); and (iii) evaluating the frequency of flooding through statistical analyses allows determining the recurrence interval for any year and for a given discharge in the stream without explicitly [14].

Every year, the Deyr (minor wet season) rains fall in Somalia, typically from September to November or December. Flooding was widespread in low-lying areas along the Shebelle and Juba rivers in late October and November 2019, and it persisted in several parts of Somalia and the Ethiopian highlands. Water levels in the Shebelle River have risen to the point that they have exceeded the town of Beletweyn's maximum holding power. Bakool, Banadir, Bay, Hiraan, Lower Juba, High Juba, and Middle Shebelle suffered the most flooding. Beledweyne district in Hiraan is one of the worst-affected areas, with nearly 70% of the town inundated. The river in Hiraan's Buklo Barte district is nearly complete, posing an immediate danger of spillage. Rainfall predictions indicate an improvement in many parts of Somalia, according to the UN Food and Agriculture Organization's (FAO) Somalia Water and Land Information Monitoring (SWALIM). The current high river levels and flash floods in Shebelle are likely to persist. More than half a million people have been affected by the flooding, with 370,000 people displaced from their homes, according to the latest estimates from the United Nations Office of Coordination for Humanitarian Affairs [15]. In addition, as the water recedes, the flooding has caused considerable damage to infrastructure, property, crops, livestock, and planting, as well as an increased risk of malnutrition and water/mosquito-borne diseases [16].

Flooding in Somalia is a major problem due to its prevalence, severity, and adverse impact on both human life and the economy. The monsoon season brings high-intensity rainfall for a short period of time, causing an abrupt surge in runoff that exceeds the drainage system's absorptive capacity and leads to flooding Ahmed et al. [17] Two types of flood occur in Somalia: Flash floods and fluvial floods [18]. Flooding occurs mainly during the Deyr (minor wet season) season and is largely affected by rainfall in the upper catchments of Ethiopia's Shebelle and Juba Rivers. Extreme floods have occurred in Somalia over the last three decades, including floods in 1997 (Deyr, minor wet season), 2006 (Deyr, minor wet season), 2018 (Gu, major wet season), and 2019 (Deyr, minor wet season). One million people were impacted by unprecedented floods in southern and central Somalia in the late months of 1997, causing significant harm to their lives and means of subsistence [19]. Li et al. [20] also reported, in 1997, Somalia experienced a devastating flood that resulted in the loss of 2311 lives and impacted approximately 1,230,000 individuals, which represented around 18% of the entire population. In Beledweyne, Somalia, the town was impacted by heavy rainfall on October 24th, 2019, which affected numerous individuals along the two main rivers of Somalia, namely Shabelle and Juba, as reported by ReliefWeb [21]. Sadiq et al. [22] used remote sensing and social sensing for flood modelling of Beledweyne town, whereas

Pulvirenti et al. [23] InSAR multitemporal data for flood modelling in Beletweyne town. Flooding in Hirshabelle, Jubaland, and Southwest states was caused by moderate to heavy rains in the Ethiopian highlands, which feed the Juba and Shebelle rivers. Strong rains of more than 100 mm fell in the Hiraan, Bay, and Bakool areas, which were already saturated from weeks of heavy rains. Moderate to heavy rains fell in parts of the Juba and Shebelle River Basins on November 4 and 5, with heavy rains falling in Beletweyn town and Wanle Weyne in Lower Shebelle and light rains falling in Nugaal and Mudug [24].

Flood hazard has been efficiently assessed using remote sensing and Geographic Information System (GIS) approaches. In hazard and vulnerability analysis, GIS overlay analysis [25], multi-criteria decision analysis [26], fuzzy method [27], and other methods have been used. Multi-criteria decision analysis (MCDA) with a Geographic Information System (GIS) is a collection of approaches for analyzing and combining geographic data and user expectations to improve decision-making. The MCDA method is frequently used to spatially reflect flood vulnerability assessments because of its adaptability in assessing various and overlapping features [28].

Flood hazard or susceptibility refers to the likelihood or probability of an area being affected by a flood, On the other hand, flood vulnerability refers to the degree of damage or negative impact that can be caused by a flood to an area or community. It takes into account factors such as the exposure of people and infrastructure to floodwaters, the resilience of the community to cope with a flood, and the potential consequences of the flood on the environment, economy, and society. It represents the susceptibility of an area to be damaged or adversely affected by a flood. Flood risk is a measure of vulnerability to damage and loss from flooding that is commonly estimated by taking into account physio-climatic, hydrodynamic, economic, social, and ecological factors. Flood risk is calculated by combining hazard and vulnerability and taking either their sum or multiplication into account [29]. Due to data constraints, the analytical calculation of flood risk is very complex and difficult. Instead, hazard assessment through numerical modeling and index-based analysis is becoming increasingly popular as a replacement for full flood risk analysis. As a result, calculating the hazard is very effective for developing and implementing a disaster mitigation strategy.

In the next section (Sect. 2), we provide an overview of the database and methodology used in our study. Section 3 presents the results of our analysis, while Sect. 4 offers a comprehensive discussion of the findings in relation to the research objectives. Finally, in Sect. 5, we draw conclusions from our study and highlight its broader implications for the field.

2 Materials and methods

2.1 Description of the study area

The Shebelle River Basin (SRB) begins in Ethiopia's highlands and flows southeast into Somalia, eventually reaching Mogadishu. It abruptly bends southwest towards Mogadishu, following the coast. Below Mogadishu, the river turns seasonal. Due to its transboundary nature, the Shebelle River Basin in southern Somalia is considered for the present study. It is located between 2° 00' 00″ N and 6° 00' 00″ N, and between 42° 00' 00″ E and 48° 00' 00″ E (Fig. 1). The river dries up at the Jubba River's mouth most of the year, but during rainy seasons, it enters the Jubba and hence the Somali Sea. On the eastern slopes of Ethiopia's highlands, the Shebelle River reaches a maximum elevation of 4230 m. The Shebelle River's catchment area is around 297,000 km^2 at its confluence with the Juba River, with two-thirds (188,700 km^2) in Ethiopia and the rest (108,300 km^2) in Somalia. The basin's elevation ranges from 20 m above sea level in the south to about three thousand meters in the east. [30]. The climate of Somalia is determined by the movement of the inter-tropical convergence zone (ITCZ) and the monsoon winds, with the coastal regions being hot and humid, and the inland areas being hot and semi-arid to arid. The annual rainfall in the northeast is below 100 mm, while the central plateaus receive between 200 and 300 mm. In contrast, the northwestern and southwestern regions receive significantly more rainfall, averaging between 510 and 610 mm per year [31]. The four distinct seasons, two of which are rainy and two of which are dry. The major rainy seasons occur between March and May, and between September and November, while the harshest dry season is from December to February and the second dry season is from June to August. The annual rainfall of SRB ranging from 200 mm to over 1500 mm, can greatly impact the drought and flood situation [19]. The 1981 floods in Somalia caused widespread damage to infrastructure and homes, while the El Niño-related floods in 1997/98 affected over a million people in various parts of the world. The 2006/07 floods in Somalia caused displacement and destruction of homes, and the 2010 floods on the Shabelle River in Somalia caused the collapse of the bridge at Belet Weyne, cutting off access to important resources and services for the affected population [32]. These examples illustrate the significant impact that flooding can have on communities, infrastructure, and the environment.

2.2 Flood inventory map

The preparation of a flood inventory map is necessary for the accurate assessment of flood susceptibility zonation. The flood inventory map of the study area was generated

Fig. 1 Geographical location for Shebelle River Basin in Somalia **a** Somalia and **b** Part of Shebelle River Basin
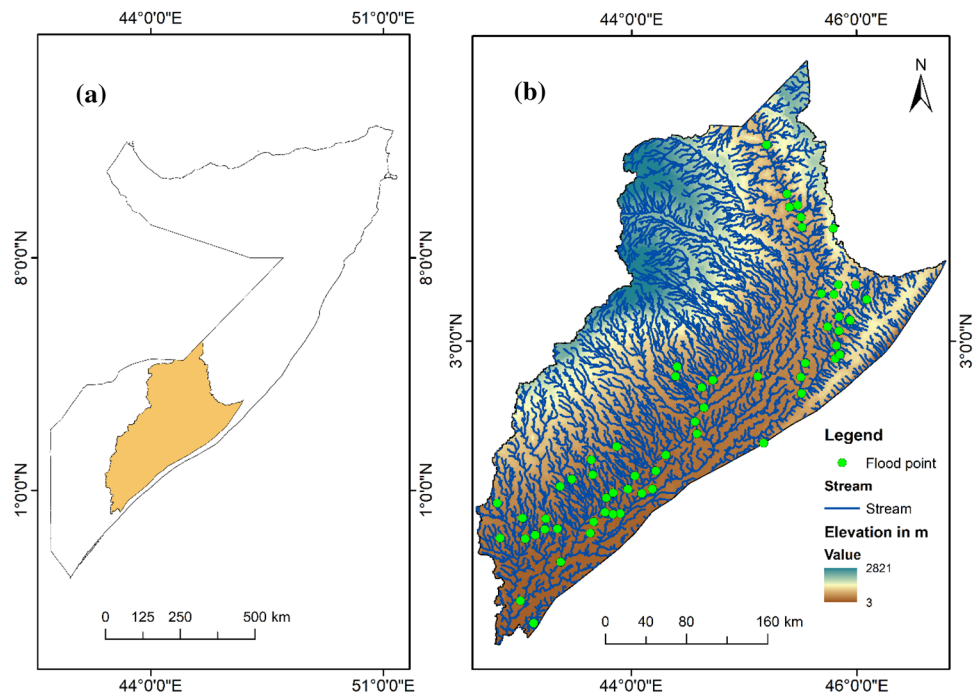
from FAO website (https://spatial.faoswalim.org/layers/?limit=20&offset=0&title__icontains=flood) from the historical flood events during 2013–2021. The flood inventory map is incorporated with the study area map in Fig. 1b. A total of 59 flood points have been identified for further analysis.

2.3 Data acquiring and preparation of thematic maps

Defining a clear and efficient methodology is vital for the quality of the findings of the study. The various input data were required to achieve the aim of this research and to have accurate results, Table 1 shows data used and their sources. In this study, secondary research data sources were used and collected through offices such as Ministry

of Energy and Water Resources, FAO, SWALIM and USGS satellite sources.

2.4 Selection of the thematic layers for flood risk zonation (FRZ)

Several multi-source geospatial datasets are required to generate a flood hazard vulnerability map for an area. The following are some of them: (i). Map of the geology; (ii). Map of the soil; (iii). 30 m Digital Elevation Model (DEM) (iv). Map of land use and cover (v) Map of population density (vi) GMIS and HBASE are two databases. These datasets were utilized to create several themed maps in the ArcGIS environment, as shown in the flow diagram in Fig. 2. The DEM was utilized to calculate relevant topographical and hydrological characteristics such as drainage density,

Table 1 Data sources used in the study

Sl No.	Data type	Source
1	Soil, Geology	Somali Water and Land Information Management (SWALIM).
2	DEM	https://search.earthdata.nasa.gov
3	LULC	https://earthexplorer.usgs.gov
4	Rainfall	https://chrsdata.eng.uci.edu/ PERSIAN CCS
5	Population density	United Nations Office of Coordination for Humanitarian Affairs (OCHA)
6	GMIS	https://sedac.ciesin.columbia.edu/data/set/ulandsat-gmis-v1
7	HBASE	https://sedac.ciesin.columbia.edu/data/set/ulandsat-hbase-v1
8	Road Network (distance to road).	https://www.openstreetmap.org/export#map=9/25.4172/85.1660

elevation, slope, and distance to river, while Land Use/ Cover was employed to create a land-use/cover map.

2.4.1 Flood hazard parameters (FHP)

The extent of flooding is influenced by a variety of factors including the physical features of the topography, rainfall, geology, drainage systems and soil texture. Through literature review and field investigation, we have considered only 7 most important parameters that contribute to flooding.

2.4.1.1 Elevation Lowland locations are more vulnerable to flooding as water moves from higher to lower elevations [33]. The elevation map is made possible by reclassifying the DEM. The Shebelle River catchment's topographic elevation ranges from 3 to 2821 m. The upstream elevation is extremely high, whereas the downstream level is extremely low. As a result of the high elevation and steep slope upstream, there is considerable runoff after heavy rains, causing high floods downstream. As a result, the land slope is flat, and the river course allows overflow.

A Digital Elevation Model (DEM) specifies the elevation of any point in a particular area at a specific spatial

Fig. 2 Methodological flow chart of the study
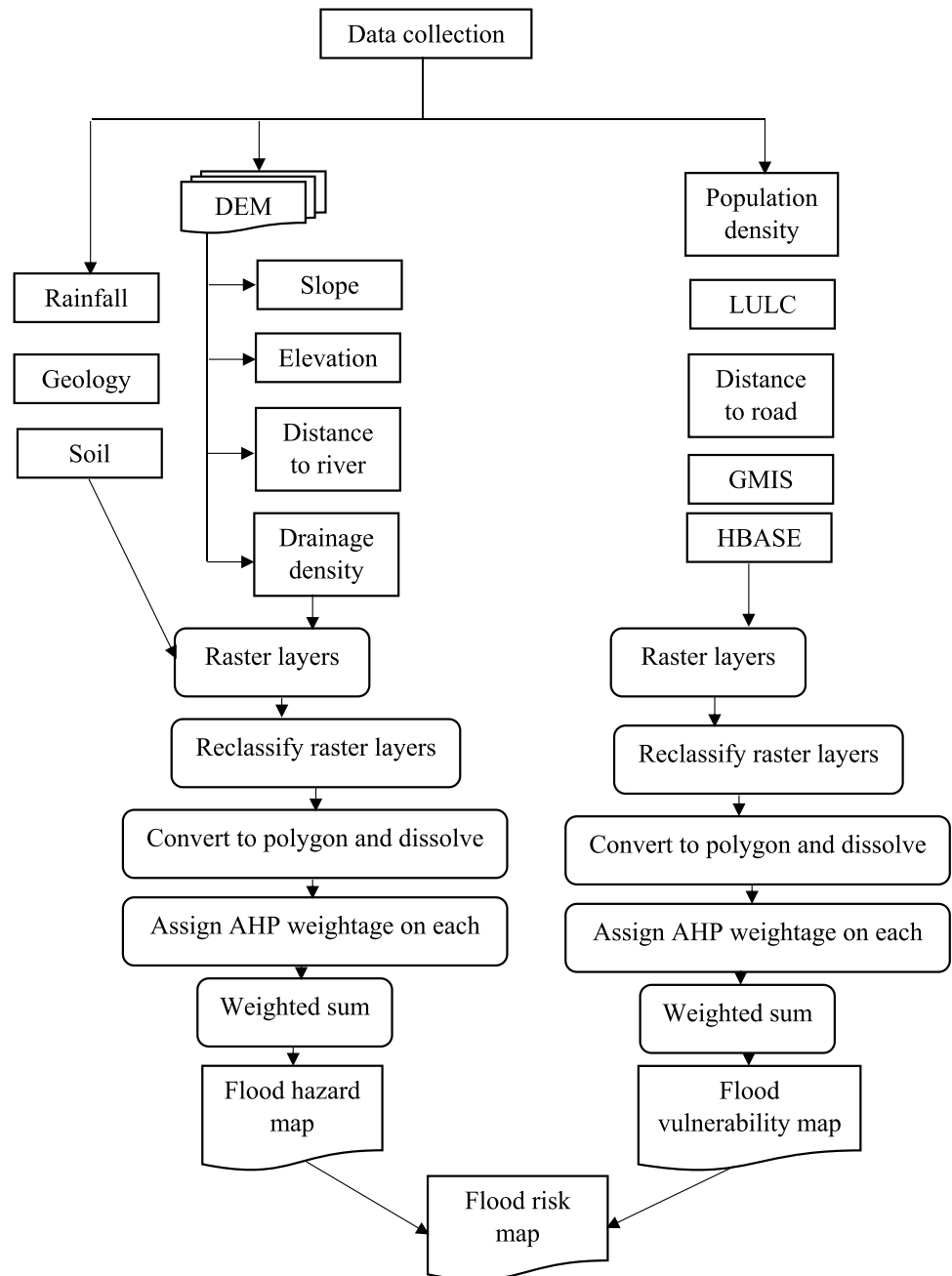
resolution as a digital file, which is used to characterize topography. For this, a DEM is required for raster-based hydrological analysis in a GIS.

The impact of the flood was categorized into different levels based on elevation. The areas with very high elevations ranging from 489 m to 2821 m were classified as having very low flood impacts. Those with elevations ranging from 340 to 488 m were classified as having low impact. Areas with elevations ranging from 220 to 339 m were classified as having moderate impact. Those with elevations ranging from 119 to 219 m were classified as having high impact. Finally, very lowland areas ranging from 3 to 118 m were classified as having very high flooding impacts (Fig. 3a).

2.4.1.2 Slope The slope is also considered another important flood-triggering parameter [34]. It has a direct impact on drainage and runoff accessibility [32]. Slope also affects the volume and velocity of surface runoff, as well as groundwater infiltration [35].

Fig. 3 Thematic layer of **a** Elevation, **b** Slope, **c** Drainage density, **d** Distance to river and **e** Annual rainfall

The classification of slope in degree scaled as follows; very high class scaled 1 (26–88), high class scaled 2 (16–25), moderate class scaled 3 (11–15), low class scaled 4 (6–10) and very low class scaled 5 (0–5) (Fig. 3b).

2.4.1.3 Drainage density One of the key variables that lead to floods is drainage density. The runoff rate is critical when the drainage density is high [35]. As a result, there is a greater chance of flooding. Dash and Sar [36] used drainage capability to integrate the combined effect of elevation and drainage density for flood hazard mapping. Flooding peaks as the drainage density increases. Many approaches have been used to determine drainage density, with the use of a computer tool (GIS software) playing a significant role. The drainage density for the Shebelle River Basin is estimated to be 0.40 km/sq.km, indicating that the basin is not particularly large and prone to flooding.

In this research, the drainage density map was divided into five classes. The very high hazard class (0.31– 0.40 km/km2), the high hazard class (0.26– 0.30 km/km2), the moderate hazard class (0.22– 0.25 km/km2), the low hazard class (0.16– 0.21 km/km2), and the very low hazard class (0.02– 0.15 km/km2) are all distinguished by a lower drainage density that is less contributed by flooding (Fig. 3c).

2.4.1.4 Distance to river In determining the flood risk zones and the flood hazard index, the distance from the river network component is crucial. Flood hazard is most severe in locations near river networks, according to [37], whereas the effect of this parameter reduces as one advances away from the riverbed.

The theme map in Arc Map 10.4.1 was separated into five categories: extremely high (0–500 m), high (501–1000 m), moderate (1001–2000 m), low (2001–3000 m), and very low (3001–8614 m) (Fig. 3d).

2.4.1.5 Rainfall The Inverse Distance Weighted (IDW) approach is used to determine the spatial distribution of this criterion. The long-term annual rainfall map is depicted in Fig. 3e. The rainfall parameter is critical in this study because it causes river overflow, which leads to flooding. As a result, high rainfall depth leads to heavy flooding, while low rainfall depth leads to low flooding.

The classification of rainfall scaled as follows; very high class scaled 1 (589-714 mm), high class scaled 2 (525-588 mm), moderate class scaled 3 (450-524 mm), low class scaled 4 (350-449 mm) and very low class scaled 5 (150–349 mm) (Fig. 3e).

2.4.1.6 Soil Understanding the many morphological and other physical aspects of the soil can be found in the soil description guideline [34]. As illustrated in the diagram
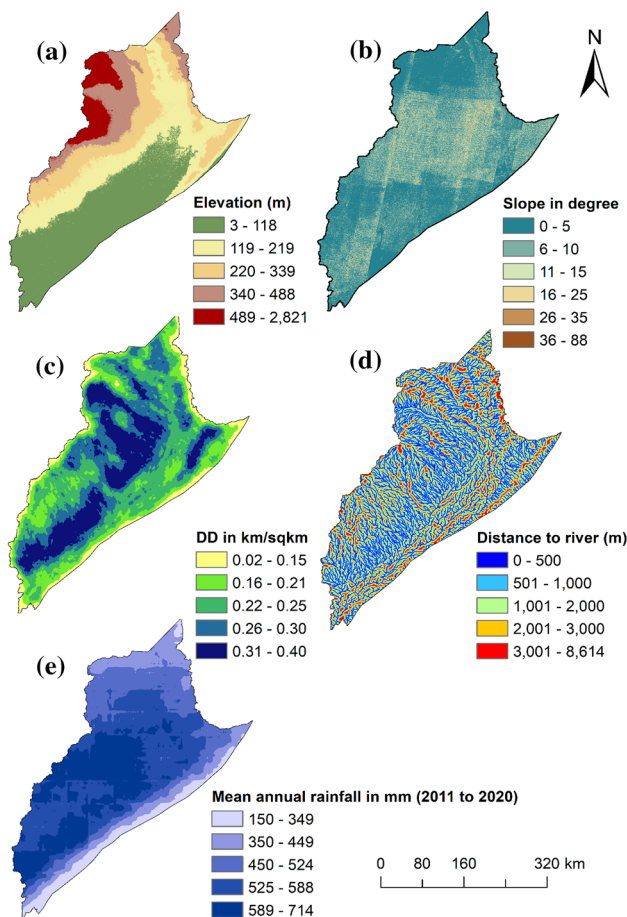
below, there were varied soil types in the Shebelle River Basin (Fig. 4). In the study area 23 distinct soil types have been found (Table 2). The Arc-GIS "To Raster" conversion tool was used to convert the soil feature type to a raster layer. As a result, the reclassification into five flood hazard levels is based on the degree to which flooding occurs.

The classification of soil degree to flooding as follows; very high class scaled 1 (Fluvisols), high class scaled 2 (Vertisols), moderate class scaled 3 (Leptosols, Luvisols), low class scale 4 (Nitosols), very low class scaled 5 (Calcisols, Cambisols, Solonchaks).

2.4.1.7 Geology The geology of the area can have an impact on flood occurrence. This is a main important flood conditioning component that contributes to the pace of flooding being amplified. Local geology keeps track of paleo-flood occurrences that can be used to estimate the frequency of prior flash floods [38].

The infiltration phase would be expedited by increased permeability lithological units, while the impermeable layer would amplify surface runoff, perhaps creating floods. The rate of infiltration and the permeability of rocks have a close relationship [39].

Rainwater infiltration is facilitated by porous formations (coarse sand, conglomerates, etc.), which reduces flood risk. Impermeable deposits (marly, clay, gypsum, etc.) on the other hand, increase runoff rates, hence increasing flood risk [40].
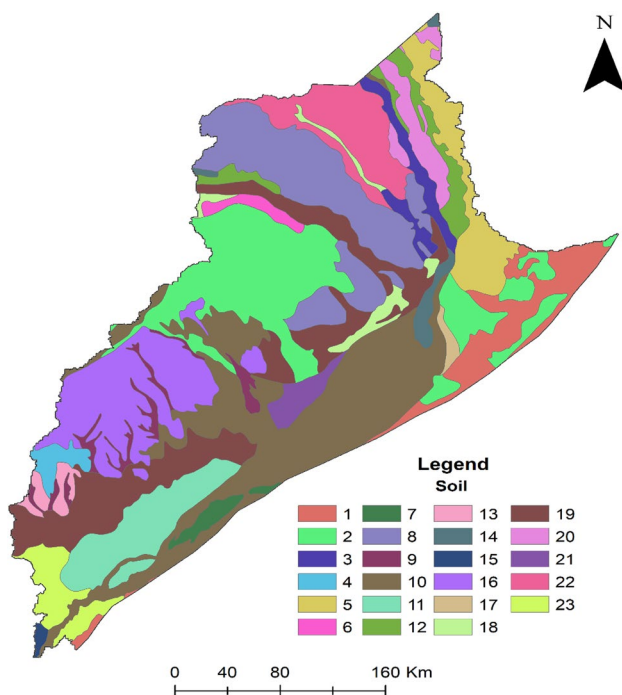
Table 2 Soil unit of the Shebelle River Basin

No.	Soil unit	Area (sq. km)
1	Calcaric Arenosols	5341.52
2	Calcaric Cambisols	15003.3
3	Calcaric Fluvisols	2057.58
4	Calcic Vertisols	1015.28
5	Cambic Arenosols	4682.34
6	Chromic Luvisols	804.203
7	Eutric Gleysols	887.795
8	Eutric Leptosols	11918.7
9	Eutric Planosols	1816.72
10	Eutric Vertisols	19115.1
11	Gleyic Solonetz	5507.3
12	Haplic Calcisols	2579.62
13	Haplic Ferralsols	943.331
14	Haplic Gypsisols	998.33
15	Haplic Luvisols	194.716
16	Haplic Nitosols	9702.4
17	Haplic Phaeozems	401.88
18	Haplic Solonchaks	1460.22
19	Haplic Solonetz	11850.2
20	Lithic Leptosols	2436.81
21	Luvic Calcisols	1284.14
22	Petric Gypsisols	5550.93
23	Sodic Solonchaks	2526.11

A total of 24 geological layers (Table 3) are divided into five categories: very high category (Silty clay), High flood hazard category (limestone and marly, limestone and clay, limestone marly and gypsum, marly and limestone), Moderate flood hazard category (alluvium, silty sediments, and quaternary sediments), Low flood hazard category (sandy clay, sands and conglomerates), Very low flood hazard category (coarse sand) (Fig. 5).

2.4.2 Flood vulnerability parameters (FVP)

2.4.2.1 Population density The population density data was provided by UNOCHA/Somalia. Vulnerability is directly related to population density since more people are exposed to dangerous events in a densely populated area [41]. The five categories on the Arc Map 10.4.1 thematic map are: very high (68–281), high (35–67), moderate (12–34), low (9–11), and very low (5–8) (Fig. 6a).

2.4.2.2 Land use land cover Because of the existing relationship between the surface parameters that affect sub-surface runoff; groundwater infiltration and debris flow, the land use parameter is strongly linked to the infiltration rate [30]. Changes in rainfall – runoff characteristics of the river basin result in changes in river flow

Fig. 4 Soil map of Shebelle River Basin

Table 3 Geology type of the Shebelle River Basin

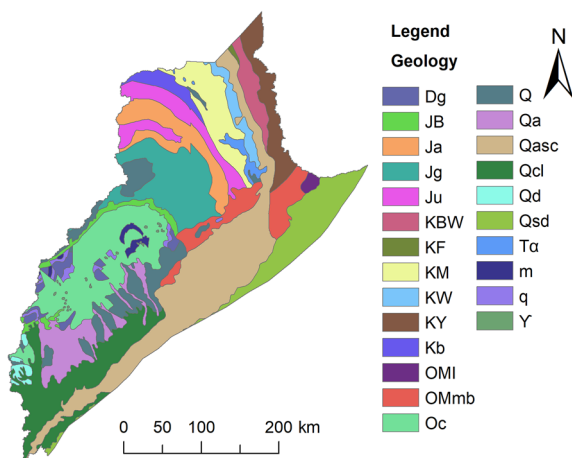| No	Geo-CODE	Geology type
1	Dg	Pelitic to psammitic paragneisses and migmatites
2	Ja	Anole (Caanoole) Fm.: marls, marly limestones, limestones and calcaresous sandstones, with ammonites, belemnites and brachiopods; mainly of open-sea environment
3	JB	Baidoa Fm.: calcarenites and limestones with pelecypods and gastropods from open to restricted platform, Aalenian to Bajocian; Waney Fm.: limestones, voricolored marls with Ammonites, and calcarenites, of shallow to open-sea environment, Late Pliensbachi
4	Jg	Goloda Fm.: Coquiniod limestones, dolomitic limestones and calcarenites; from supratidal to shallow shelf environment
5	Ju	Uegit (Wajid) Fm.: fossiliferous limestones, locally Oolithic, calcarenites, marls and sandstones; from shallow shelf to lagoonal environment
6	Kb	Garbahare Fm; Busul Member, Algal dolomitic limestones, lime stones, calarenities and fluvial sandstones. Passes literally to KM
7	KBW	Belet Weyne Limestones: subtidal micritic limestones with some sandstones, rich in pelecypods and gastropods
8	KF	Ferfer Gypsum: gypsum with sandy and marly intercalations
9	KM	Main Gypsum Fm.: gypsum with shales, dolomites,limestones and marls
10	KW	Mustahil Limestone: limestones and marls, with rudists and corals
11	KY	Yesomma sandstones: variegated quartzose sandstones, mainly fluvial
12	m	Marbles
13	Oc	Migmatites, paragneisses, minor amphibolites Ca-silicate felses and quartzites
14	OMI	Limestones, sandstones and siltstones of shallow marine environment
15	OMmb	Gypsiferous sands and sandy clays, limestones, basalts found in wells (continental "Mudug Beds")
16	q	Quartzites, locally iron-rich and banded
17	Q	Sands, silts and gravels: alluvial, colluvial, eluvial, eolian and beach deposits
18	Qa	Sands, silts and gravels: alluvial, colluvial, eluvial, eolian and beach deposits
19	Qasc	Silty clays, sands and gravels: alluvial deposits of the Jubba and Webi Shabelle rivers
20	Qcl	Predominant dark grey clays with sands, fluvial to subordinately lagoonal
21	Qd	White, fine sands, mainly deltaic
22	Qsd	Sand dunes and beach deposits
23	Tα	Basalt flows, tuffs and sills
24	ϒ	Pelitic to psammitic paragneisses and migmatites

Fig. 5 Geological map of Shebelle River Basin

regimes as a result of changes in natural land use land cover [30]. Land use and land cover data from SWALIM (Somali Water and Land Information Management) revealed that agricultural land, scrub, bare ground, built-up area, water body, and vegetation covered a substantial portion of the investigated area.

They were assessed and ranked from very low to very high flood vulnerability using the Spatial Analyst Tool (SAT) with GIS. Forests favor infiltration and have low flooding, whereas agricultural regions allow more water to flow as surface or subsurface runoff and have high flooding. Vegetation cover, built-up area, agricultural area, water bodies, and barren ground were the five categories of LULC in the research region. The agricultural land took up the most acreage, 50.62%, while the built-up area took up the least, roughly 0.07% (Fig. 6b).

2.4.2.3 Distance to roads Another crucial criterion in assessing flood-prone zones is the distance of any area from the road. By restricting the entry of water into the earth, roads actually slow down the infiltration process. As a result, locations with a dense network of roads are
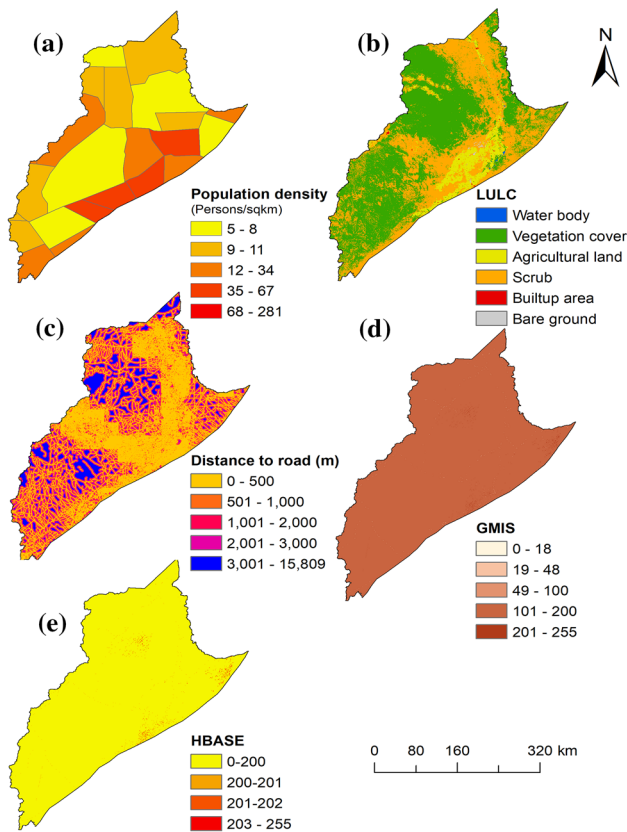
Fig. 6 Thematic layer of **a** Population Density, **b** Land use and Land cover, **c** Distance to Road, **d** GMIS and **e** HBASE

overwhelmed by low-intensity rain, resulting in flooding.

Furthermore, due to reduced infiltration and a speedier runoff process, areas next to the road are more vulnerable to flooding. In this study, it classified as follows; very high class scaled 1 (0-500 m), high class scaled 2 (501 m-1,000 m), moderate class scaled 3 (1001- 2000 m), low class scaled 4 (2,001 m-3,000 m) and very low class scaled 5 (3001–15,809 m) (Fig. 6c).

2.4.2.4 GMIS (global man-made impervious surface) Asphalt, sand, stone, concrete, bricks, glass, and other manmade materials are used to create water-repellent surfaces that prevent water from penetrating the soil [9]. Flooding is more likely when impervious surfaces enable more water to flow as surface or subsurface runoff. As the classification it classified as follows; very high class scaled 1 (200–255), high class scaled 2 (100–200), moderate class scaled 3 (48–100), low class scaled 4 (18–48) and very low class scaled 5 (0–18) (Fig. 6d).

2.4.2.5 HBASE (Human built-up area settlement extent) Urban areas are rapidly encroaching on agricul-

tural and grassland areas that act as natural flood retention zones. This poses significant issues in terms of flood water management in urbanized locations [42]. As the classification it classified as follows; high class scaled 2 (202–255), moderate class scaled 3 (201–202), low class scaled 4 (200–201) and very low class scaled 5 (0–200) (Fig. 6e).

2.5 Analytical Hierarchy process

Saaty first developed AHP, a practical and extensively used multi-criteria decision technique, in 1980. It's commonly used to rank factors in order to identify which is the most important, according to expert opinion [43]. For the development of flood susceptible and vulnerable areas, there were a total of twelve flood-influencing factors identified in this study. Therefore, using Saaty's scale of preference between 1 and 9 (Table S1), and based on literature review, field knowledge, and studies in similar geographical regions, the relative weight of each layer has been determined.

2.5.1 Pairwise comparison matrix

Based on the chosen flood contributing criteria, a pairwise comparison matrix table was created. Following that, based on the Expert's assessment, each aspect was given a specific weight. The scale relative importance was used to assign relative relevance or value, as illustrated in Table S2. It's worth mentioning that the number of elements employed in the study matches to the length of the comparison matrix table. The comparison matrix table was used to determine factor weight, class weight, and the CR value. The following expression is used to calculate the CR value [44]:

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

2.5.2 Consistency index (CI)

The rule of transitivity is widely used to check for consistency in outcomes. The following expression is used to calculate the value of λmax:

$$\lambda \max = \sum_{n}^{n} a_{ij} \frac{w_j}{w_i} = n \tag{2}$$

The resultant CR value determines the matrix's consistency. A value of > 0 indicates that the matrix is unreliable, whereas CR = 0 indicates that the matrix is reliable. The great majority of the time, max is not equal to n. As

a result, we evaluated CI to see if it matched the transitivity condition. The following equation was used to determine CI:

$$CI = \frac{\lambda max - n}{n - 1} \tag{3}$$

2.5.3 Flood risk

The combination of flood hazards and vulnerabilities at a specific site is known as flood risk. As a result, systematic assessment, collection, and analysis of variables are required. Because it allows for the development of maps inundated areas, GIS has become an important tool in flood mapping and analysis [11]

$$Risk = Hazard\ index \times Vulnerability\ index \tag{4}$$

The study weighted the various thematic indicator classes and layers based on their significance and contribution to the hazard and vulnerability. The overlay technique was used on the indications to evaluate hazard and vulnerability first, then cross hazard and vulnerability to identify and zone flood risk areas. The raster calculator in the spatial analyst tools was used to carry out all of the operations in ArcGIS.

The prepared flood hazard, vulnerability and risk maps have been classified into five classes viz. very low, low, medium, high and very high using natural break method.

3 Results

3.1 Analyzing of flood influencing factors for creating flood hazard mapping

The flood hazard map was developed using seven primary flood influencing parameters (elevation (E), slope (SL), drainage density (DD), distance to river (DR), and yearly rainfall (R), geology (G), soil (S)). A comparison matrix table (Table S2) was built for this study to compare these factors

and sub factors. Table 4 show the normalized vector for the flood hazard thematic layers. We also developed the random index among the factor and sub factors in this regard.

The CR value was then calculated, obtaining a resultant CR value of 0.069. As a result, it is reasonable to conclude that such elements and sub-elements can be considered in AHP analysis. Table 5 shows the relative importance of each element and its sub-elements in the study. In determining flood-prone zones, height (40.4%) was the most critical element, as shown in Table 5.

As a result, the most essential factor in determining flood-prone areas may be elevation. The next most important characteristics that have a substantial impact on determining flood-prone locations are slope (22.6%), drainage density (11.7%), and distance to river (11.5%). Rainfall (6.9%), geology (4.3%), and soil (2.5%), on the other hand, were found to be the least affected components in the study. All of these factors had little impact on the development of the study area's flood susceptibility map.

Arc GIS software was used to develop Flood hazard mapping. The flood prone area was found using the catchment-Response Approach to flood hazard. The causes that cause floods differ from one study to the next. Elevation, slope, rainfall, drainage density, distance to river, geology, and soil are the selected flood generating parameters for this study.

The spatial Analyst Tool (SAT) reclassified the raster format based on the degree of flooding. Based on flood hazard, these components were reclassified into five danger levels (very low hazard level, low flood hazard, moderate flood hazard, high flood hazard, and very high flood hazard), with each parameter rate assigned to a separate flood hazard group. Personal judgment, local knowledge, professional expertise, and data from prior studies are used to determine the degree of flood generating elements that cause floods.

Flooding occurs more quickly in flat places than in sloped locations where runoff runs further down. The slope of terrain, which is the most frequently and generally known topographic size element, is a parameter that

Table 4 Normalized vector for flood hazard zonation in Shebelle River Basin

Parameters	E	SL	DD	DR	R	G	S	Average
Elevation	0.464	0.577	0.464	0.424	0.341	0.288	0.273	**0.404**
Slope	0.155	0.192	0.278	0.339	0.227	0.205	0.182	**0.226**
Drainage density	0.093	0.064	0.093	0.085	0.171	0.164	0.152	**0.117**
Distance to river	0.093	0.048	0.093	0.085	0.171	0.164	0.152	**0.115**
Rainfall	0.077	0.048	0.031	0.028	0.057	0.123	0.121	**0.069**
Geology	0.066	0.038	0.023	0.021	0.019	0.041	0.091	**0.043**
Soil	0.052	0.032	0.019	0.017	0.014	0.014	0.030	**0.025**
Sum	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**

Table 5 Weightage of each factor and sub-factors in developing flood susceptible map of Shebelle River Basin

SL No.	Factors	AHP for each factor	Sub factors	Descriptive level (flood hazard)	Area (Km^2)	Area in %	AHP weight for sub factor
1	Elevation	0.404	488–2,821 m	Very low	39,859.1	36.88	0.416
			340–487 m	Low	26,959.8	24.94	0.262
			220–339 m	Moderate	20,304.6	18.79	0.161
			119–219 m	High	13,392.0	12.39	0.099
			(-70–118 m)	Very high	7563.1	7.00	0.062
2	Slope	0.226	26°-88°	Very high	59,778.1	55.31	0.430
			16°–25°	High	31,787.1	29.41	0.288
			11°–15°	Moderate	11,051.1	10.23	0.123
			6°–10°	Low	4768.5	4.41	0.079
			0°–5°	Very low	693.8	0.64	0.081
3	Drainage density	0.117	0.31–0.40 km/km^2	Very high	8411.0	7.78	0.050
			0.26–0.30 km/km^2	High	18,154.0	16.80	0.088
			0.22–0.25 km/km^2	Moderate	33,001.5	30.53	0.151
			0.16–0.21 km/km^2	Low	26,657.7	24.67	0.259
			0.02–0.15 km/km^2	Very low	21,854.5	20.22	0.451
4	Distance to river	0.115	0–500 m	Very high	27,140.6	25.11	0.503
			501–1000 m	High	24,478.1	22.65	0.260
			1001–2000 m	Moderate	33,770.1	31.25	0.134
			2001–3000 m	Low	16,366.4	15.14	0.068
			3001–8614 m	Very low	6323.3	5.85	0.035
5	Rainfall	0.069	589–714 mm	Very high	7802.8	7.22	0.053
			525–588 mm	High	14,243.4	13.18	0.089
			450–524 mm	Moderate	22,080.5	20.43	0.153
			350–449 mm	Low	35,945.9	33.26	0.262
			150–349 mm	Very low	28,006.1	25.91	0.444
6	Geology	0.043	VH	Very high	9619.32	8.92	0.416
			H	High	1698.41	1.58	0.262
			M	Moderate	26,233.93	24.33	0.161
			L	Low	55,138.52	51.14	0.099
			VL	Very low	15,124.53	14.03	0.062
7	Soil	0.025	VH	Very high	47,912.8	44.33	0.503
			H	High	11,918.7	11.03	0.260
			M	Moderate	16,225.0	15.01	0.134
			L	Low	24,990.5	23.12	0.068
			VL	Very low	7031.7	6.51	0.035

may be generated from additional study of Digital Elevation Model (DEM) for further analysis. The processing of digital elevation models (DEM) with the program Arc Map resulted in the slope of the study area map (Spatial Analyst Extension).

3.1.1 Weighted coefficients

The flood generating parameters employed in this study their pair wise to determine flood hazard priorities, which were calculated using the Analytical Hierarch approach (AHP). Following repeating iteration until the desired consistency ratio is less than 10% or 0.1, a pair-wise comparison of one factor to another is performed. The consistency ratio for this study was 6.9% or 0.069, which is less than 10% or 0.1, which is considered acceptable. The resultant weight is given by the decision matrix, which is based on the major eigenvector.

3.2 Flood hazard mapping

This research developed a flood hazard map by integrating the seven flood affected strata, similar to other flood hazard researches [45, 46]. Furthermore, different researches

only have four or six components [47–49]. However, using more than six components is generally suggested to decrease the risk of over-rating some aspects due to non-representative ratings controlled by a single factor [50]. According to the literature, there is no common rule for automatically identifying class borders; instead, most studies use their own knowledge and expertise to do so [51].

Flood-prone areas, according to many experts, have a mix of very low elevation, low slope, and high drainage density [52, 53]. Using the natural breaking slope approach in the "ArcGIS 10.4.1 environment," the hazard was divided into five main groups: very high, high, moderate, low, and very low hazard zones.

The flood hazard maps were created using secondary data and the AHP reclassification technique for seven sub-criteria. The final flood hazard map developed using the AHP-GIS technique contained 13.04% and 21.95% areas classified as very high and high flood hazard, 29.13% areas classified as medium flood hazard, and 24.97% and 10.92% areas classified as low and very low flood hazard, respectively.

Figure 7a shows that the blue color denotes very low flood hazard, the blue light color denotes low flood hazard, the green color denotes medium flood hazard, the yellow color denotes high flood hazard, and the brown color denotes very high flood hazard.

3.2.1 Weighted Sum

Weighting strategies are used to rank the relative value of each factor in relation to another. In weighted overlay, the higher the weight, the more essential the component is in comparison to the other factors. The final flood hazard map was created by overlapping the aforementioned seven floods and their associated coefficients for the Shebelle River. Flood Hazard = 0.404 * Elevation + 0.117 * Drainage Density + 0.115 * Distance to River + 0.226 * Slope + 0.069* Rainfall + 0.043 * Geology + 0.025 * Soil.

3.3 Analysing of flood influencing factors for creating flood vulnerability mapping

The flood vulnerability map was developed using five primary flood contributing parameters (population density (PD), landuse and landcover (LULC), distance to road (DR), global man-made impervious surface (GMIS), and human built-up and settlement extent (HBASE)). A comparison matrix table (Table S3) was built for this study to compare these factors and sub-factors. Then it was normalized and eigenvector was calculated (Table 6). We also calculated the random index among the factor and sub-factors in this regard.
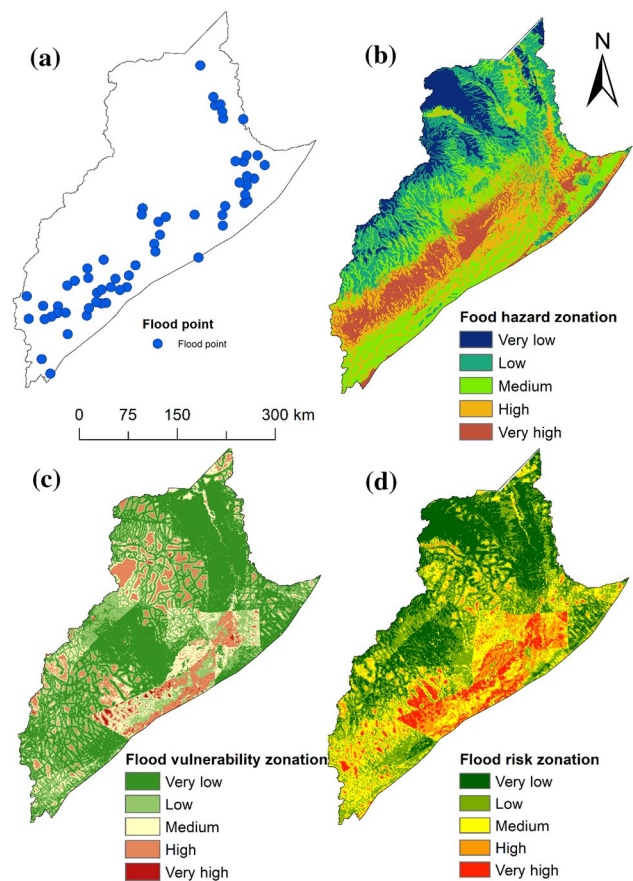

Fig. 7 Flood mapping of Shebelle River Basin **a** Flood Inventory map **b** Flood hazard mapping using AHP of Shebelle River Basin **c** Flood Vulnerability mapping and **d** Flood risk mapping

After that, the CR value was calculated, and the resultant CR value was 0.019. As a result, it is reasonable to assert that such components and sub-factors can be taken into account for AHP analysis. The relative importance of each element and its sub-factors in the study is represented in.

Table 7 shows that the most important element in predicting flood vulnerable zones was population density (31.1%).

As a result, the most important element in defining flood-prone locations may be population density. After population density, the next most important characteristics that play a significant influence in predicting flood sensitive areas are LULC (28.5%), distance to road (21.7%), and GMIS (11.2%). However, HBASE (7.5%) was shown to be the least influenced element in the study.

Thematic layers such as population density, land use/land cover, road distance, GMIS, and HBASE were combined to create the flood vulnerability map. Expert opinion and previous case studies are used to allocate the elements that affect flood-prone locations, as well as their

Table 6 Normalized vector for flood vulnerability

Parameters	PD	LULC	DR	GMIS	HBASE	Average
PD	0.316	0.279	0.414	0.316	0.231	**0.311**
LULC	0.316	0.279	0.207	0.316	0.308	**0.285**
DR	0.158	0.279	0.207	0.211	0.231	**0.217**
GMIS	0.105	0.093	0.103	0.105	0.154	**0.112**
HBASE	0.105	0.070	0.069	0.053	0.077	**0.075**
Sum	1	1	1	1	1	1

Table 7 Weightage of each factor and sub factors in developing flood vulnerable map of Shebelle River Basin

SL no	Factors	AHP for each factor	Sub factors	Descriptive level (flood vulnerable)	Area (Km²)	Area (%)	AHP weight for sub factor
1	Population density	0.311	68–281	Very high	42,150.6	39.00	0.044
			35–67	High	31,489.1	29.14	0.084
			12–34	Moderate	21,056.8	19.48	0.148
			9–11	Low	13,373.2	12.37	0.256
			5–8	Very low	9.3	7.00	0.467
2	Distance to road	0.217	0–500 m	Very high	50,709.2	46.92	0.044
			501–1000 m	High	20,190.3	18.68	0.084
			1,001–2,000 m	Moderate	19,474.6	18.02	0.148
			2,001–3,000 m	Low	8817.1	8.16	0.256
			3,001–15,809 m	Very low	8887.5	8.22	0.467
3	HBASE	0.075	202–255	High	107,692.3	99.64	0.096
			201–202	Moderate	8.3	0.01	0.161
			200–201	Low	77.0	0.07	0.277
			0–200	Very low	301.1	0.28	0.466
4	GMIS	0.112	200–255	Very high	43.3	0.04	0.035
			100–200	High	27.5	0.03	0.068
			48–100	Moderate	14.5	0.01	0.134
			18–48	Low	107,692.3	99.64	0.260
			0–18	Very low	301.1	0.28	0.503
5	LULC	0.285	Built up area	Very high	78.9	0.07	0.430
			Agricultural area	High	54,704.8	50.62	0.288
			Vegetation cover	Moderate	7923.7	7.33	0.123
			Bare ground	Low	44,994.7	41.63	0.079
			Water body	Very low	376.5	0.35	0.081

weightings. Flood vulnerability is divided into five categories based on the cumulative vulnerability score: very low, low, moderate, high, and very high.

The flood vulnerability maps were created using secondary data and the AHP reclassification technique for 5 sub-criteria. The final flood vulnerability map calculated using the AHP-GIS technique showed 0.65% and 11.42% of places classified as very high and high flood vulnerable, 12.67% as medium flood vulnerable, and 29.28% and 45.98% as low and very low flood vulnerable.

3.3.1 Weighted coefficients

The flood generating parameters employed in this study their pair wise to determine flood vulnerability priorities, which were calculated using the Analytical Hierarch approach (AHP). Following repeating iteration until the desired consistency ratio is less than 10% or 0.1, a pairwise comparison of one factor to another is performed. The consistency ratio for this study was 1.9% or 0.019, which is less than 10% or 0.1, which is considered acceptable. The resultant weight is given by the decision matrix, which is based on the major eigenvector.

3.4 Flood vulnerability mapping

The five flood impacting layers were used to create a flood vulnerability map in this study. The obtained vulnerability was divided into five groups based on the natural breaking approach in the "ArcGIS 10.4.1 environment": very high, high, moderate, low, and very low vulnerable zones.

The flood vulnerability maps were created using secondary data and the AHP reclassification technique for 5 sub-criteria. The AHP-GIS technique produced a final flood vulnerability map with 0.65% and 11.42% of places classified as very high and high flood hazard, 12.67% as medium flood hazard, and 29.28% and 45.98% as low and very low flood hazard, respectively.

Figure 7b shows that the blue color denotes very low flood hazard, the blue light color denotes low flood hazard, the green color denotes medium flood hazard, the yellow color denotes high flood hazard, and the brown color denotes very high flood hazard.

3.4.1 Weighted sum

Weighting strategies are used to rank the relative value of each factor in relation to another. In weighted overlay, the higher the weight, the more essential the component is in comparison to the other factors. The final flood vulnerability map was created by overlapping the aforementioned five floods and their associated coefficients for the Shebelle River. Flood Vulnerability (FV) = PD*0.311 + LULC*0.285 + DR*0.217 + GMIS*0.112 + HBASE*0.075.

3.5 Flood risk mapping

The final result of the present study is the flood risk zonation (FRZ) map, which is a combination of the flood hazard zone (FHZ) map and the flood vulnerability zone (FVZ) map. The risk of flooding is depicted on a map that shows five levels of risk, ranging from very low to very high (Fig. 7c). The final flood risk map created using the AHP-GIS technique comprised 5.7% and 12.13% areas classified as very high and high flood risk, 23.65% areas classified as medium flood risk, and 30.88% and 27.64% areas classified as low and very low flood risk. Most of the high and very high flood risk zone falls in the coastal areas, especially in Jilib, Baraawe, Marka and Wanlaweyne districts.

3.6 Validation of the model

The study quantitatively verified the AHP output with the flood inventory map through ROC-AUC. The ROC-AUC has been performed by comparing the FHZ map with 59 flood points employing the 'ArcSDM' tool in the ArcGIS software. Figure 8 manifests the ROC curves and AUC for
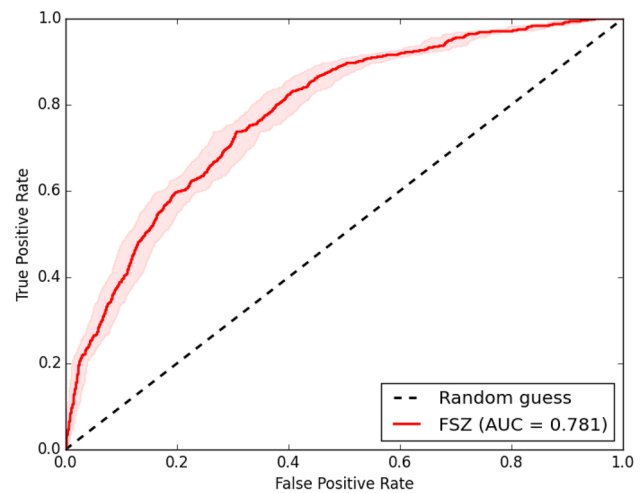
Fig. 8 Receiver operating characteristics (ROC) curve

the AHP model. The AUC displayed the accuracy rate of the FHZ model, which can be categorized into four groups, i.e., excellent (> 0.9), accepted (0.8–0.9), good (0.7–0.8), and considerable (0.5–0.7). The study revealed that the observed accuracy of the AHP technique is 0.781 (78.10%). Therefore, according to the satisfaction scale, the model is efficiently performed to produce the FHZ map, and it is considered a good outcome.

4 Discussion

The present study on flood risk assessment in the lower part of the Shebelle River Basin in Somalia using the GIS-based AHP method. The study aimed to determine the flood-prone areas in the basin by analyzing seven primary flood influencing parameters: elevation, soil, drainage density, slope, geology, distance to river, and annual rainfall. The weighted coefficients were used to determine the priority of flood hazard parameters by calculating pairwise comparisons using the AHP method. The flood hazard map was developed using the AHP-GIS technique by integrating the seven flood affected strata, and flood vulnerability map was prepared by integrating five important factors such as population density, LULC, distance to road, GMIS, and HBASE. Finally, flood risk map was prepared and the natural breaking approach was used to divide the risk into five main groups: very high, high, moderate, low, and very low risk zones. The final flood risk map contained 5.7% and 12.13% areas classified as very high and high flood risk, 23.65% areas classified as medium flood risk, and 30.88% and 27.64% areas classified as low and very low flood risk, respectively. The results of the study indicated that elevation was the most critical element in determining flood-prone areas, followed by slope, drainage density, and

distance to river. Rainfall, geology, and soil were found to be the least affected components in the study. According Muchiri [54] the rainfall of the basin less than 100 to 600 mm, but it is transformed into surface water flow, which is then directed through the watershed by utilizing the natural slope of the terrain to connect adjacent cells along the path of maximum descent, resulting in the flood occurrences. Another study showed, over the past twenty years, Shebelle River Basin has seen a rise in the occurrence of severe, destructive floods that have led to numerous deaths and impacted the lives of thousands of individuals [18]. Parvez et al. [16] urged that floods impact and needs assessment should prioritize the needs of vulnerable populations, including children, elderly, disabled individuals, and low-income households, in order to ensure equitable and effective disaster response and recovery efforts in Somalia. But previous flood hazard assessment studies used an index-based approach based on only climatic parameters [55], digital elevation model (DEM)-derived geomorphological and hydrological characteristics [18], land use and urbanization information, economic activity, infrastructure, and demographic aspects [17]. However, assessing spatial flood risk is critical for providing early warning and disaster risk reduction. Furthermore, MCDA incorporates stakeholder interests in the form of parameter weights, resulting in a solution for a multidimensional problem like flood vulnerability, which may be seen from economic, physical, social, and environmental perspectives. Therefore, the findings may help local governments and decision-makers in their efforts to mitigate catastrophic risks of flood, they can be invaluable in promoting resilience and saving lives and property in the face of disasters. The study can be useful for disaster management and planning authorities to identify areas that are most prone to flooding and to take necessary precautions and measures to minimize the damage caused by floods.

5 Conclusions

The objective of this study was to prepare flood hazard, vulnerability, and risk maps in a specific part of the Shebelle River Basin of Somalia by analyzing flood-triggering factors using the GIS-based AHP technique. By using Arc GIS software, the following flood-generating parameters were created during the development of flood hazard, vulnerability and risk map; Elevation, Slope, Soil, Geology, Distance to river, Rainfall, Drainage density, Land use/Land cover, Population density, Distance to road, GMIS and HBASE maps. Different indicators are used to generate the flood hazard and

vulnerability layers, and AHP is used to assign weightage to each indicator. The final flood risk map is created using GIS software that combines hazard and vulnerability zonation. A combination of a hazard map (elevation, slope, drainage density, distance to river, yearly rainfall, geology, and soil type) and vulnerability map was necessary for the multi-criteria analysis approach utilized in mapping flood-prone areas (population density, land use land cover, distance to road, GMIS and HBASE). According to the map, 17.82% of the study area is at risk of flooding at a high and very high level, 23.64% is at risk of moderate flooding, and 58.52% is at risk of low and very low flooding. As a result, in the face of climate change, decision-makers can use this map as a reference for potential preventive activities, better land use planning, and flood risk management. To form a study viewpoint that might improve and refine the data produced, the locations classified as high and very high risk require further extensive mapping using high spatial resolution satellite images. This study also has shown the accuracy and indisputable role of geoformation approaches in natural catastrophe analyzing, which necessitates the use of multi-source data.

Declarations

involved in the work. The manuscript has not been submitted to any other journal nor is it under consideration in any other journal.

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