

Research

Flood risk assessment under the shared socioeconomic pathways: a case of electricity bulk supply points in Greater Accra, Ghana

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Abstract

This study evaluates flood susceptibility and risk on Bulk Supply Points in the Greater Accra region (GAR) using a Frequency Ratio model based on 15 flood conditioning factors. The model explores the influence of natural, meteorological and anthropogenic factors on flooding occurrences under the Shared Socioeconomic Pathway (SSP) scenarios and assesses flood risks at Bulk Supply Points (BSPs). Flood susceptibility mapping was conducted for both current and future periods under various SSP scenarios. Results reveal that elevation, slope, soil type, distance from urban areas, and SPI are the most influential factors contributing to flooding susceptibility in the region. The current flood map, about 37% of the total area of GAR categorized under the moderate flood-susceptible zone category followed by about 30% categorized under the low flood-vulnerable zone. However, about 16% was categorized under the very high flood-vulnerable zone. The study projects increasing flood susceptibility under the SSP scenarios with intensification under SSP2 and SSP3 scenarios. For instance, the areas categorized as high and very high flood susceptibility zones are projected to expand to approximately 32% and 26% each by 2055 under SSP3. The study also assesses flood risks at Bulk Supply Points (BSPs), highlighting the escalating susceptibility of power assets to flooding under different scenarios. For instance, in the very high scenario, flooding is estimated to reach 640 h in 2045 and exceed 800 h in 2055—more than double the 2020 baseline. The analysis shows the bulk supply points face increasing flood susceptibility, with risks escalating most sharply under the severe climate change SSP3 and SSP5 scenarios. Over 75% of BSPs are expected to fall in the low- to medium-risk categories across SSPs while more than 50% of BSPs are within medium- to high-risk categories in all scenarios except SSP1, reflecting the impact of climate change. SSP3 and SSP5 stand out with over 60% of BSPs facing high or very high flooding risks by 2055. It indicates moderate resilience with proper adaptation but highlights potential disruptions in critical infrastructure, such as BSPs, during persistent flooding. The findings of the study are expected to inform Ghana's contributions towards addressing Sustainable Development Goals (SDGs) 7, 11 and 13 in Ghana.

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1 Introduction

Over the years, various forms of natural and anthropogenically-induced disasters, such as earthquakes, landslides, hurricanes, volcanic eruptions, and floods, amongst others, have occurred [1–3]. Floods are natural disasters caused by an overflow of a large volume of water above its usual limits, resulting in temporary inundation of river banks and stagnant water [4]. It is one of the most common types of natural/man-made disasters that interrupts anthropogenic activities, destroys properties and causes loss of life. Moreover, floods are known to destroy environmental ecosystems, disrupt agricultural activities and socio-cultural hereditament [5–9]. Globally, floods are noted to be a tragic and sudden event, resulting in huge wealth and health losses.

Sarkar and Mondal [4] noted that from 1963 to 1992, floods had caused about 32% of damage to the environment and humans. Currently, floods have resulted in the loss of 100,000 lives globally, affecting approximately 2 billion people and causing damages estimated at around \$651 billion [10]. The African continent is the second-most vulnerable continent to floods after Asia in terms of the frequency of events, magnitude of affected areas and lives lost [11, 12]. Most countries in Africa have had a taste of awful flood-related disasters in the recent past. For instance, Mozambique recorded one of the most devastating floods in February and March 2000 amongst flood events in the last 50 years [13]. Again, the 2007 flood event which affected countries such as Togo, Mali, Burkina Faso, Niger, Uganda, Sudan and Ethiopia killed more than 500 people while displacing several millions of inhabitants [14].

The UN regional Coordinator in Dakar revealed that the July 2007 flood event in West Africa was the most tragic flood event in the last 30 years. As a result of the flood event, more than 210,000 and 785,000 people were killed and displaced, respectively. Again, about 600,000 inhabitants were affected after torrential rains in 16 West African countries where Ghana, Burkina Faso, Niger and Senegal were the most affected. Aside from this, Nigeria in 2012 recorded one of the most catastrophic flood events ever observed, which resulted in the displacement and death of 2.3 million and 363 people, respectively [15].

The existence of perennial urban flooding in Ghana dates back to 1930 [16]. At least about 18 out of the last 50 years have observed substantial flood events where properties and lives have been lost [16–19]. The study of Douglas et al. [13] revealed that the occurrence of flood events in the coastal areas of Ghana has increased since 1995, resulting in the displacement and death of about 34,076 and 14 people, respectively. This also led to the property losses of about \$168,289, as estimated by the National Disaster Management Organization (NADMO) [1].

Flooding has a significant impact on power systems. It can lead to long outage times and the destruction of power system equipment such as substations, transmission lines, and power plants [20]. In recent years, flooding has had devastating impacts on power infrastructure in many parts of the world, often leaving large populations without electricity for extended periods [21–23]. The Greater Accra region of Ghana has experienced several major flood events in the past decade, which have damaged key power assets and caused widespread blackouts across the capital city of Accra and surrounding areas [1, 24]. With climate change projections indicating increased variability and severity of extreme rainfall events in West Africa [7], there are growing concerns about the resilience of Ghana's power sector infrastructure to future flooding.

Flooding is of particular concern for the bulk supply points (BSPs) that deliver electricity from generating plants to end users in the Greater Accra region. These facilities, operated by the Ghana Grid Company (GRIDCo), contain vital transformers, switching gear and control equipment. Flood damage to BSPs can disrupt the entire downstream supply chain, affecting hospitals, businesses, homes, and other critical services. In 2015, major flooding of a GRIDCo substation in Achimota left many parts of Accra without power for several days [1]. With a growing population and electricity demand, along with the country's dependence on hydroelectric generation, Ghana's power sector is vulnerable to increases in extreme precipitation and flooding resulting from climate change. Therefore, this article examines the current and future flood risks facing the bulk supply point (BSPs) in the Greater Accra region. It assesses the exposure and susceptibility of these power infrastructures while exploring potential adaptation strategies to enhance resilience against future climate change impacts.

Therefore, mapping flood susceptibility to design management schemes can combat the destruction of BSPs in the future and be used to direct governments and policymakers to establish appropriate flood management strategies.

Geographical information system (GIS) and remote sensing (RS) techniques now have the capacity to support a new understanding of the assessment of susceptibility with better justification [4]. The analysis of satellite images through GIS and RS offers promising results for flood susceptibility mapping as it reveals flawless information about a specific area [25]. Several studies have successfully employed GIS and RS techniques in flood susceptibility assessment with different models [26–28]. The Frequency ratio (FR) model is a widely used technique with high overall accuracy [29]. The FR model uses bivariate statistical analysis to assign values to each class of each parameter and estimate its impact on flood occurrence [3, 29]. GIS and RS software offers a straightforward approach for mapping flood susceptibility using FR.

Other studies have employed various robust methodologies to map flood susceptibility. For instance, previous studies [30–34] utilized the Analytical Hierarchy Process (AHP) effectively in their flood susceptibility mapping efforts. Additionally, the Multi-Criteria Decision Support Approach (MCDA) has been implemented by [31, 35, 36]. Other methodologies like Weights of Evidence (WofE) as seen in Rahmati et al. [9], adaptive neuro-fuzzy interface systems such as Sezer et al. [37], and artificial neural networks (ANN) like those used by Tiwari & Chatterjee [38] have also been applied in various studies. While AHP remains the most commonly utilized approach, it is constrained by uncertainties stemming from user-provided information [39]. MCDA, on the other hand, is valued for its utility in flood mapping in data-scarce regions, often employed by local planners [40]. ANN attempts to establish relationships between flood conditioning factors and outcomes, yet its reliance on user inputs can introduce uncertainties in its predictions [41]. Recently, approaches like FR and WofE have emerged in flood susceptibility mapping, although they have predominantly been applied in other natural hazard mappings such as landslide studies [9, 42–44].

Several studies have generally mapped flood susceptibility in the Greater Accra region. However, most of these studies were limited to only the Accra metropolitan area. For example, Dekongmen et al. [45] studied flood vulnerability in Accra by analyzing natural factors like elevation, drainage density, and slope. However, their focus was restricted to these factors within the Accra metropolis alone, excluding the broader region. Similarly, other studies by [17, 36, 46–48] concentrated on flood susceptibility mapping specifically within the Accra metropolitan area. In contrast, Kwang and Osei [30], Njomaba et al. [49], and Kumi-Boateng [31] extended their investigations to cover almost the entire Greater Accra region, except for the Ada East and West districts. Nevertheless, these studies primarily mapped current flood susceptibility and did not include future flood projections under different climate scenarios, such as the Shared Socioeconomic Pathway scenarios (SSP), which remain largely unexplored in the region. Moreover, there are limited or no studies on the impacts of floods on bulk power supply points in Ghana's Greater Accra region. This presents a unique gap to investigate the impacts of flooding on BSPs and their related effects on power denial under the shared socio-economic pathway (SSP) scenarios. The findings of this study are expected to add knowledge to existing studies on the impacts of flooding in Greater Accra, especially on BSPs. Moreover, the findings of this study are expected to inform future adaptation strategies of different organizations, such as electricity distribution companies, NADMO and the various assemblies in different districts to manage floods under different scenarios better. Finally, the findings are expected to inform Ghana's contributions towards addressing Sustainable Development Goals (SDGs) 7, 11 and 13 in Ghana.

2 Materials and methods

2.1 Description of the study area

Greater Accra spans approximately 3,245 km² and is home to around 5,455,692 people according to the Ghana Statistical Service [50]. Positioned between Latitude 5°30' to 5°53' North and Longitude 0°03' to 0°25' West, this area exhibits occasional hills and lowlands, averaging about 20 m above sea level. The terrain generally maintains gentle slopes of about 11%, except for specific areas like Abokobi, Kwabenya, and the McCarthy hills, where slopes can exceed 22%. The water table in Greater Accra is situated between depths of 4.80 to 70 m below the surface [46]. Within the anomalous dry equatorial climatic region, Greater Accra experiences dual peaks of precipitation and a prolonged dry season, occasionally marked by dry Harmattan conditions. February and March are the hottest months, averaging around 27 °C monthly [50]. Conversely, the coldest months fall between June and August, with an average monthly temperature of approximately 21 °C (Ghana Statistical Service, 2014). Precipitation is characterized by two peaks: a major season from March to July and a minor one from September to November, totaling an annual precipitation range of 780–1200 mm [51], while the Ghana Meteorological Agency reports an average precipitation of about 812 mm [51]. Vegetation in the studied area comprises two primary types: coastal scrub and grasslands, alongside mangrove forests. The coastal scrub and grasslands, observed in specific Greater Accra locations, feature intermittent tree patches, including Baobab and

Neem trees. Mangrove forests, found in coastal lagoon areas with salty and waterlogged soil, delineate a distinct habitat. Figure 1 displays a map of the studied area.

In the Greater Accra region, flooding is a recurring concern, particularly in low-lying areas and zones with poor drainage systems. Heavy rainfall during the peak seasons, compounded by the region’s topography and land use, often leads to inundation and waterlogging. The lack of adequate infrastructure and urban planning exacerbates this issue, making some areas prone to flash floods and subsequent damage to property and livelihoods. Additionally, the encroachment on waterways and wetlands further contributes to the region’s susceptibility to flooding incidents. Addressing these challenges requires comprehensive flood mitigation strategies, improved drainage systems, and sustainable urban development practices to minimize the impact of flooding in Greater Accra.

2.2 Data sources and flood conditioning factors

The detailed specifications of the datasets used in the study are presented in Table 1, showing various types and sources. These datasets were used in generating layers of flood conditioning factors utilized in the FR model. Future precipitation data for different SSP scenarios in Greater Accra was sourced from the study of Siabi et al. [51]. Land use and land cover (LULC) changes under SSP scenarios were modeled using the GeoSOS-FLUS [52] software, based on the 2020 LULC map for Greater Accra. GeoSOS-FLUS integrates natural and human influences for simulating multi-type land use scenarios. Urban data, both current and future under SSP scenarios, were extracted from the respective LULC maps. Stream data was derived from the Shuttle Radar Topographic Mission (SRTM) digital elevation model (DEM) data, while road data

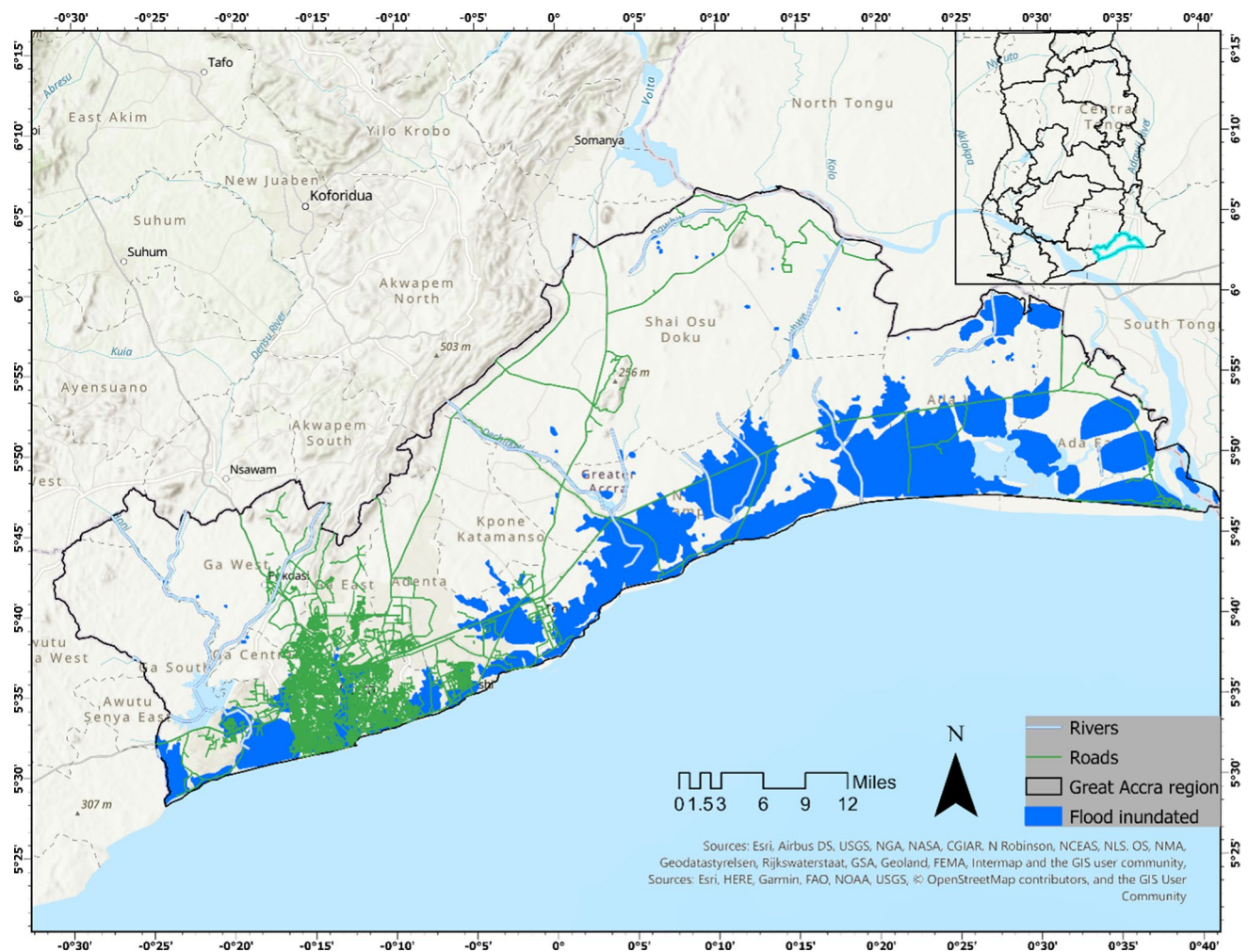


Fig. 1 Study area map

Table 1 Sources and type of data used

Description of data	Data type/ resolution	Year	Source
Landsat 8 LULC map	30 m	2020	Author generated
Future LULC	30 m	2020–2055	Author generated
SRTM DEM	90 m	2020	USGS
Stream	Raster	2020	Extracted from DEM
Geology	Raster	2020	Ghana Geological Survey Authority
Road	Raster	2020	Extracted from Google open street
Precipitation	Raster	2020	GMet
Future precipitation	Raster	2020–2055	Siabi et al. [51]
Urban data	Raster	2020	Retrieved from LULC map 2020
Future Urban data	Raster	2020–2055	Retrieved from LULC maps 2020–2055
Flood inventory data	Vector	2015–2019	NADMO/Literature/field survey [14, 17–19, 46, 55]

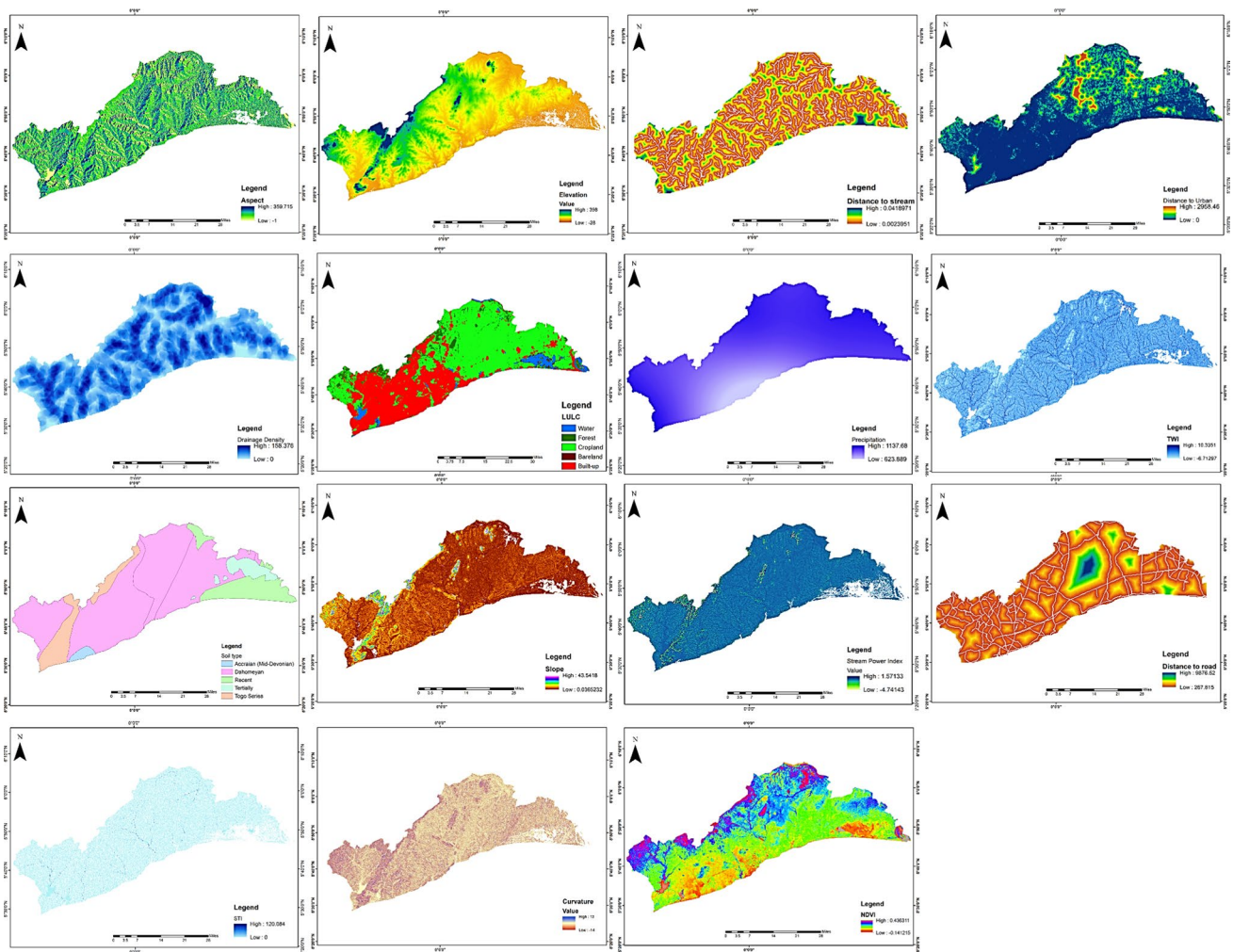


Fig. 2 Flood conditioning factors used for the study

was obtained from Google Open Street Maps [53]. Elevation, slope, and topographic wetness index (TWI) were extracted from the SRTM DEM [54]. These datasets collectively formed the flood conditioning factors (Fig. 2).

2.2.1 Elevation

Elevation is a key factor affecting flooding, with lower elevations generally experiencing a higher risk of flooding [54]. The study area, with elevations ranging from – 21 to 398 m above mean sea level (MSL), was divided into five elevation classes. Analysis of the elevation map indicates that the region predominantly consists of very low-lying areas within this range (Fig. 2). The predominance of these low elevations significantly contributes to the flood risk in the study area.

2.2.2 Slope

Slope is a crucial factor in hydrology, with a direct relationship to surface runoff and a significant impact on flooding [55]. The slope of the study area, measured in degrees from the processed DEM, was reclassified accordingly. Typically, areas with low elevation feature gentle or flat slopes, making them more prone to flooding and waterlogging (Fig. 2). Steeper slopes, on the other hand, increase water velocity, leading to faster runoff. Conversely, flat or gently sloping terrain allows runoff to disperse more gradually [56]. As a result, low-gradient slopes in lower elevations are more susceptible to flooding compared to steeper, high-gradient areas. The elevation and resulting slope exhibit minimal spatial variation due to historical changes in the study area.

2.2.3 Curvature

Curvature offers important insights into the terrain's geomorphological characteristics [57]. Plan curvature data, extracted from the DEM, was classified into three categories: concave, flat, and convex (Fig. 2). In the study area, 19.19% of the land has a concave curvature, 48.63% is flat, and 32.16% is convex.

2.2.4 TWI (Topographic Wetness Index) and SPI (Stream Power Index)

TWI and SPI are critical hydrological factors commonly used in flood studies. TWI (Topographic Wetness Index) maps the spatial distribution of moisture, influencing surface runoff patterns [40], whereas SPI (Stream Power Index) measures the erosive potential of surface runoff [58].

2.2.5 Soil type/Geology

In this study, geology is regarded as a key conditioning factor due to its direct impact on the ground's water absorption capacity [59]. Geological data for the region was sourced from the Ghana Geological Survey Authority. The study area includes five distinct geological units (Fig. 2), with Accranian geology being the most prevalent. Terrains with this geological composition are susceptible to rapid runoff, which heightens the risk of severe flooding downstream, especially during heavy rainfall events.

2.2.6 Land use land cover

In susceptibility mapping, understanding the spatial distribution of Land Use and Land Cover (LULC) is crucial for identifying which land use types and activities are most affected by frequent flooding. Different LULC categories, such as croplands, bare lands, and built-up areas, particularly in low-lying regions, can significantly influence flood occurrence and severity. For instance, areas with extensive croplands may experience increased runoff due to soil disruption, while bare lands offer minimal absorption and can lead to heightened surface runoff. Built-up areas, especially in flood-prone zones, often have impervious surfaces that exacerbate flooding by preventing natural water absorption [3]. The LULC information for the study area, which highlights these factors, is detailed in Fig. 2. This information is vital for assessing flood risk and implementing effective land management strategies.

2.2.7 Distance from stream and drainage density

Proximity to natural drainage is a critical conditioning factor due to its substantial impact on flooding. Areas located near natural drainage systems, such as streams and rivers, are more prone to flooding because these water bodies can quickly convey excess water during heavy rainfall. The distance from streams is an important aspect to consider; regions closer to streams are at a higher risk of flooding compared to those further away. This is because the closer proximity allows for less time for water to dissipate, leading to quicker accumulation and higher flood risks in these areas. Drainage density, which measures the extent of stream networks within the study area, also plays a crucial role in flood events. A higher drainage density, with numerous and densely packed streams, can exacerbate flooding by increasing the volume and speed of surface runoff. Areas with a high drainage density often experience more frequent and severe floods due to the efficient and rapid channeling of water from rainfall into streams and rivers. Figure 2 provides a detailed map showing both the distances from streams and the drainage density across the region. This information is essential for understanding how proximity to natural drainage and drainage density contribute to flood risk, aiding in the development of effective flood management strategies.

2.2.8 Distance from urban and roads

The distance from urban areas and roads is a vital factor in assessing flood susceptibility in the Greater Accra region of Ghana. Urbanization significantly alters the region's hydrological dynamics, influencing its susceptibility to flooding. Analyzing how proximity to urban centers and transportation networks affects flood risk is essential for effective flood risk management and mitigation. Urbanization tends to increase flood risks through multiple mechanisms. The expansion of built-up areas does not only result in more impervious surfaces, but also lead to issues such as improper solid waste disposal into drainage systems, which can clog and impair their functionality, construction activities, especially in or near waterways, can further disrupt natural water flow and exacerbate flooding as well as informal activities in unplanned urban areas—such as unauthorized encroachments, and illegal dumping can severely affect drainage systems and water flow patterns. These activities can redirect or concentrate runoff towards areas not adequately prepared for high volumes of water, increasing the likelihood of severe flooding. Figure 2 shows the spatial distribution of distances from urban areas and roads.

2.2.9 NDVI

In evaluating flood susceptibility, the Normalized Difference Vegetation Index (NDVI) is crucial for assessing land cover and land use changes. NDVI values range from -1 to 1 , with higher values reflecting healthier and denser vegetation (Fig. 2). Healthy vegetation, indicated by elevated NDVI values, enhances soil stability through root systems that bind the soil, reduce erosion, and improve water absorption. In flood-prone areas, robust vegetation can help mitigate the effects of heavy rainfall by promoting natural drainage and reducing surface runoff. NDVI is also instrumental in identifying and delineating floodplains. Areas with lower NDVI values, such as barren land or urbanized regions, typically exhibit reduced vegetation density and may be more vulnerable to flooding. By incorporating NDVI data into floodplain mapping, authorities can better identify high-risk areas and implement targeted flood mitigation strategies. This integration supports more effective flood management by highlighting areas where vegetation can play a critical role in flood prevention and management.

2.2.10 Aspect

The aspect, or the direction a slope faces, is a key factor in flood susceptibility within the region of Ghana (Fig. 2). Analyzing the aspect of terrain offers important understandings into water runoff patterns and their impact on flooding risk and also identify how different slope orientations affect water accumulation and runoff behavior. For example, low-lying areas with certain slope aspects may be more prone to water accumulation, especially during heavy rainfall. Conversely, slopes oriented in directions that facilitate rapid runoff can increase the likelihood of flash

floods in downstream areas. Therefore, evaluating aspect data is crucial for identifying areas at greater risk of flooding and for implementing appropriate flood management strategies.

2.3 Flood inventory

For flood susceptibility mapping, it is imperative to consider historical flood occurrence data that is scientifically justified to forecast future floods [60]. The accuracy and reliability of the forecasted flood susceptibility rely on the correctness of historical flooding events [4]. Flood inventory data from 2015 to 2019 was obtained from the field survey, NADMO and literature [14, 17–19, 46, 61]. The study used a sum of 384 flood points. These points were randomly divided into training and validation of the developed flood model; 70% and 30% of the flood points were used for training and testing the final model, respectively. Several studies have employed this same structure in the training and authentication of their models [8, 9, 60]. However, there are no specific rules for defining how flood points are divided into training and validation [29]. Figure 3 presents the flood inventory map of the Greater Accra region.

2.4 Frequency ratio model

The evaluation of flood susceptibility is relevant to discover the conditioning factors of floods. The association between the occurrence of flooding and the related conditioning factors can be detected based on historical flooding events and their causative factors. The study utilizes the FR model in generating the flood susceptibility maps for Greater Accra under the SSP scenarios. The FR model is a bivariate statistical analysis technique that critically analyzes the contribution of each

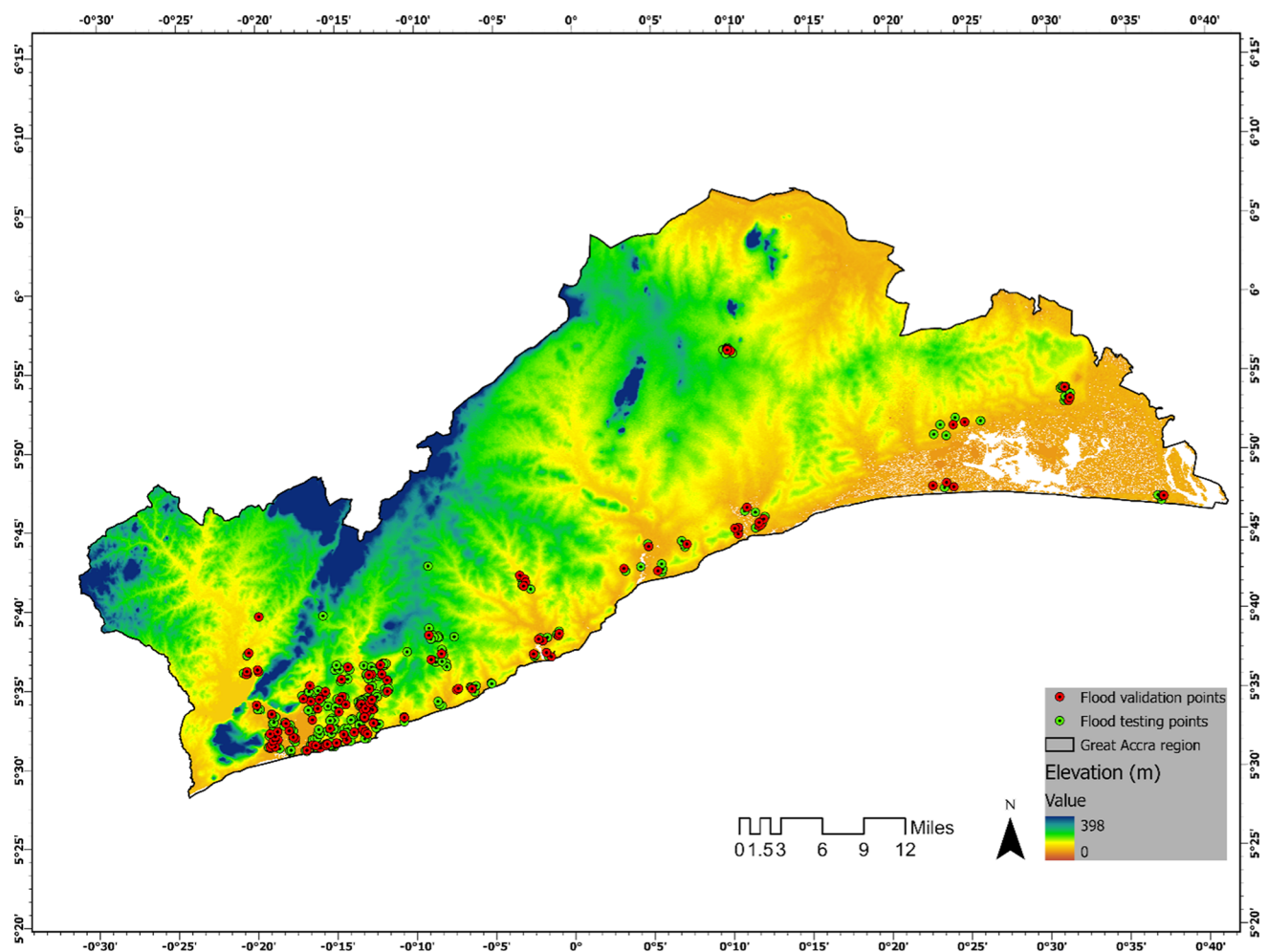


Fig. 3 Greater Accra Flood inventory map

class of each flood conditioning factor on future flooding [30]. FR (see Eq. 1) is estimated by analyzing the association between flood events and the contributing factors. Therefore, FR [62, 63] is given as:

$$FR = \frac{\left[\frac{N_{pix}(X_i)}{\sum_{j=1}^m X_j} \right]}{\left[\frac{N_{pix}(X_j)}{\sum_{j=1}^n N_{pix}(X_j)} \right]} \quad (1)$$

where $N_{pix}(X_i)$ = number of flood points in class i of variable X ; $N_{pix}(X_j)$ =the number of pixels in variable X_j ; m = total classes in the variable X_j ; n = total factors of the study area.

An FR value greater than 1 indicates significant parameters that strongly contribute to flooding. Conversely, an FR value less than 1 signifies an inverse relationship between flood occurrence and the conditioning factors [41, 64–67].

After the estimation of the FR for every class, all values for each conditioning factor are summed for generating the final flood susceptibility map. The formula for the final flood susceptibility index (FSI) (see Eq. 2) is given as:

$$FSI = \sum_{j=1}^n FR \quad (2)$$

The FR approach has been successfully applied for flood susceptibility mapping globally [4, 8, 9, 26]. However, prediction rate is calculated as

$$= (\text{Max } RF^i - \text{Min } RF^i) - Q$$

where RF = relative frequency and defined as the FR value per class divided by the sum of FR values for an input parameter; $\text{Max } RF^i$ = the Maximum relative frequency value of i th parameter; $\text{Min } RF^i$ = the Minimum relative frequency value of i th parameter; Q = the lowest difference ($\text{Max } RF^i - \text{Min } RF^i$) attained by an input parameter compared to all other parameters.

2.5 Model validation

The receiver operating characteristic (ROC) curve [68] was used to validate the baseline flood susceptibility map. The ROC curve is a scientific and general technique of assessing the accuracy of a model. In the ROC curve, the X and Y axes show the false and true positive rates, respectively. To substantiate the prediction of models, the area under the curve (AUC) is considered. An AUC value of less than 0.50 is considered unsatisfactory for flood susceptibility mapping. A perfect model is attained when the AUC is 1. Therefore, the model is defined as poor when the AUC is between 0.5 and 0.6. The model is good when the AUC is between 0.7 and 0.8, and the model is very good and excellent when AUC is between 0.8–0.9 and 0.9–1, respectively.

2.6 Methodological roadmap for the flood susceptibility mapping

Figure 4 shows the methodological roadmap for generating current and future flood susceptibility maps of Greater Accra. The flood conditioning factors were categorized into natural and anthropogenic factors. The preprocessing stage initially involved clipping and reclassifying all datasets to the study area into five subclasses. Subsequently, thematic layers were created for each factor, all standardized to a spatial resolution of 30 m, consistent with the LULC data resolution. A flood inventory map was developed using historical flood data sourced from field surveys, NADMO, and literature (Table 1). This, combined with future layers such as distance from urban areas, precipitation, and LULC under SSP scenarios, constituted the input data for the FR model (see Fig. 2). The baseline flood susceptibility map generated by the FR model was validated and assessed for performance using Receiver Operating Characteristic-Area under the curve (ROC-AUC). If the model performed well, future flood susceptibility maps were produced. If performance was inadequate, the model underwent recalibration until satisfactory validation scores were achieved. For forecasting future floods under SSP scenarios, all flood conditioning factors were kept constant except for variable factors like precipitation, LULC changes, and distance from urban areas (Table 1).

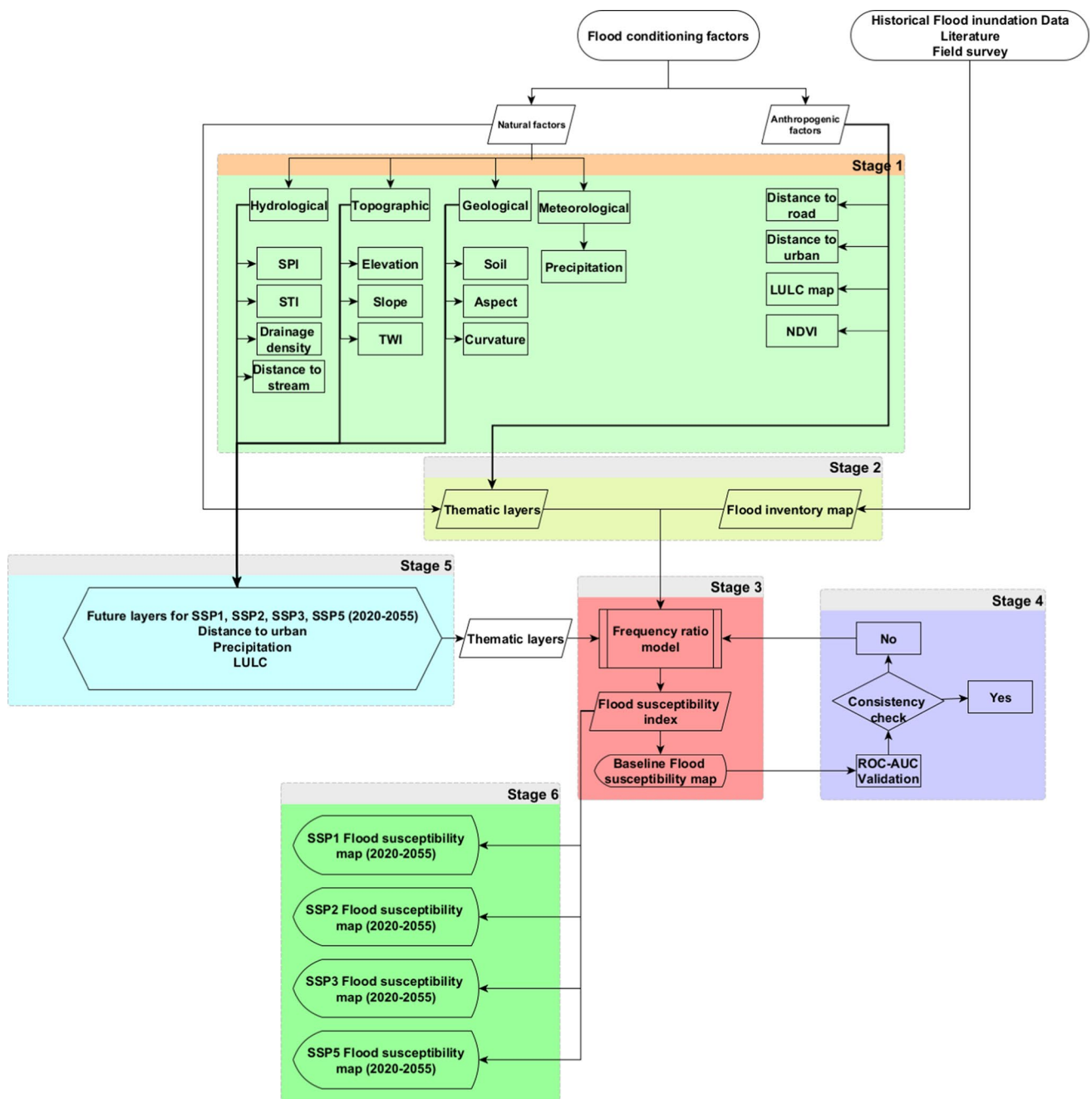


Fig. 4 Methodological flowchart for flood susceptibility mapping

2.7 Flood exposure analysis

Historical precipitation data from 1991 to 2020 was obtained from the World Climate Guide to determine average monthly rainfall days in Accra [69]. A typical 8-h flooding duration from a heavy rainfall event was estimated based on prior hydrologic analysis by Ansah et al. [70]. This 8-h duration was adjusted by ± 2 h to represent moderate and very heavy rainfall events, respectively, according to USGS rainfall intensity classifications [71].

Future rainfall intensification under each SSP scenario was quantified using the prediction rates of influential flood conditioning factors (precipitation, land cover, and distance from urban areas) from the frequency ratio flood

model results. The relative increase in these factors compared to 2020 baseline levels was used to scale the typical 8-h flooding duration each month and estimate future flood duration hours through to 2055.

2.8 Annual electricity supply potential

The locations of 45 electricity bulk supply points (BSPs) in Greater Accra were mapped in GIS software using data obtained from GRIDCo and the Electricity Company of Ghana (ECG), as presented in Appendix 3. The capacity and average annual availability of each BSP facility were compiled based on information from the electricity distribution companies. Availability factors of 0.85 accounting for maintenance downtime were applied to estimate each BSP's annual electricity supply potential in MWh based on its capacity in MW.

$$\text{Supply(MWh)} = \text{Capacity(MW)} \times \text{Operating time(h)} \times \text{Availability factor(\%)} \quad (3)$$

2.9 Power denial estimation

We define power denial in this context to mean power not available to consumers due to the shutdown of a flooded BSP. Flood susceptibility maps were used to identify BSP susceptibility to flood which is crucial for a comprehensive risk assessment. While flood depth and duration are primary factors in determining potential inundation, the use of flood susceptibility maps provided additional critical insights by incorporating multiple flood conditioning factors such as elevation, land cover, and drainage density. This multidimensional approach enhanced the predictive accuracy of flood risks, which informs strategic planning for infrastructure resilience under different climate scenarios. The flood duration estimated each month per SSP scenario were assumed to represent BSP outage times during an extreme flooding event to quantify power denial in Eq. (4). The outage time was multiplied by the capacity to estimate power denial in MWh for each BSP (see Appendix 3). Results were summed across all BSPs to determine total power denial in Greater Accra under each future flooding scenario.

$$\text{Power denied (MWh)} = \text{Capacity (MW)} \times \text{Outage time (h)} \quad (4)$$

3 Results

3.1 FR values for flood conditioning factors

Table 2 presents the weights of the various sub-classes of the 16 flood conditioning factors used in the FR model. FR values for flood conditioning factors, such as elevation, slope, precipitation, TWI, STI, SPI, and drainage density, have been estimated using the FR model (see Appendix 1). High SPI values between 0.21–0.04 and 0.03 – 1.57 had FR values that are considerably greater than one (Table 2). This implies that, the higher SPI the higher the probability of occurrence of flood. Similarly, FR values tend to increase as precipitation increases. For instance, precipitation subclasses between 948–1018 mm (FR = 1.13) and 1018–1137 mm (FR = 1.06) recorded FR values that are greater than one (see Table 2). This signifies high probability of flood occurrence in high rainfall areas of the region.

For distance from stream, areas with distance between 0.0024 and 0.0053 m to stream recorded an FR value of 1.34. This signifies that as the distance decreases from a stream, the FR value increases leading to a high probability of flooding in these areas. Likewise, FR values tend to increase as distance from urban areas decreases. For instance, areas with distance between 1–72.56 and 72.56–141.87 m from urban recorded 1.08 and 1.33 FR values, respectively, showing a high probability of flooding in these areas (Table 2). Distance from urbanization is one of the major contributors of flooding events. Urban areas are known for their concretization, which prevents rainwater from seeping into the ground; as a result, surface runoff is accelerated, leading to flooding in areas where draining systems are not big enough to handle the flow accumulation.

From Table 2, the FR values are more than one where NDVI is between – 0.14 and 0.15, signifying no or unhealthy vegetation with higher chances of flooding (see Table 2). NDVI, which shows the health of vegetation, may contribute to flooding since areas where there is no or unhealthy vegetation has a greater chance for flooding. Moreover, LULC sub-classes such as water (FR = 1.94), cropland (1.04) and bareland (2.03) had FR values that is more than 1, compared to

Table 2 Features and FR results of flood factors

Factors	Classes	Total pixel (km ²)	% of area	Total flood pixel (km ²)	% of area	FR
Stream Power Index (SPI)	– 4.74 to 1.42	1049	0.261	4	0.004	0.016
	– 1.42 to 0.61	4990	1.239	55	0.057	0.046
	0.61–0.21	41,711	10.360	6798	7.089	0.684
	0.21–0.04	179,819	44.664	45,555	47.508	1.064
	0.03–1.57	175,033	43.475	43,478	45.342	1.043
Precipitation (mm)	623.88–762.91	30,324	7.067	13,758	3.471	0.491
	762.91–861.64	45,998	10.720	11,769	9.024	0.842
	861.64–948.28	67,467	15.724	14,759	15.481	0.985
	948.28–1018.80	98,925	23.055	28,333	26.172	1.135
	1018.80–1137.67	186,369	43.434	39,638	45.852	1.056
Distance from stream (m)	0.022–0.042	6266	1.657	1975	1.090	0.658
	0.015–0.022	41,034	10.848	5695	6.366	0.587
	0.01–0.015	81,857	21.641	13,274	14.838	0.686
	0.0053–0.01	110,640	29.251	24,687	28.713	0.982
	0.0024–0.0053	138,449	36.603	43,829	48.993	1.338
Distance from urban (m)	281.91–359.71	15,045	3.505	46	0.042	0.012
	209.77–281.91	26,932	6.274	714	0.658	0.105
	141.87–209.77	46,273	10.780	9189	8.471	0.786
	72.56–141.87	89,163	20.773	29,993	27.649	1.331
	1–72.56	251,818	58.667	68,537	63.180	1.077
Normalized Difference Vegetation Index (NDVI)	0.264–0.436	47,654	11.107	3962	3.649	0.329
	0.203–0.264	133,523	31.120	21,658	19.948	0.641
	0.150–0.203	141,812	33.052	45,587	41.987	1.270
	0.094–0.150	91,856	21.409	30,034	27.662	1.292
Landuse Land cover (LULC) 2020	– 0.14 to 0.09	14,208	3.311	7334	6.755	2.040
	Water	16,604	3.871	8153	7.517	1.942
	Forest	24,147	5.630	2402	2.215	0.393
	Cropland	225,280	52.525	59,228	54.608	1.040
	Bareland	2824	0.658	1447	1.334	2.026
Drainage density	Built-up	160,047	37.316	37,230	34.326	0.920
	59.06–99.74	89,984	20.980	16,781	15.576	0.742
	41.46–59.06	118,472	27.622	23,931	22.213	0.804
	26.99–41.46	101,969	23.774	25,596	23.758	0.999
	13.3–26.99	81,719	19.053	28,457	26.414	1.386
Slope	0.001–13.3	36,765	8.572	12,970	12.039	1.404
	16.03–43.54	1450	0.356	3	0.003	0.008
	8.40–16.07	5748	1.410	42	0.041	0.029
	3.62–8.40	16,065	3.940	456	0.450	0.114
	1.23–3.62	140,607	34.483	24,432	24.129	0.700
Curvature	0.036–1.23	243,887	59.812	76,324	75.377	1.260
	– 13 to 2.02	6032	1.447	3	0.003	0.002
	– 2.02 to 1.04	18,463	4.432	4	0.004	0.016
	– 1.04 to 0.04	62,533	14.709	20,765	19.199	1.003
	0.04–1.02	209,269	49.456	52,594	48.635	1.024
	1.02–12	126,849	29.956	34,778	32.159	0.983

Table 2 (continued)

Factors	Classes	Total pixel (km ²)	% of area	Total flood pixel (km ²)	% of area	FR
Aspect	–1 to 73.56	68,811	16.700	14,819	14.141	1.141
	72.56–141.87	81,012	19.662	21,456	20.474	0.814
	141.87–209.77	87,322	21.193	24,747	23.615	0.847
	209.77–281.91	96,054	23.312	24,183	23.077	0.990
	281.91–359.71	78,833	19.133	19,589	18.693	0.977
Topographic Wetness Index (TWI)	– 6.71 to 2.97	129,318	31.714	20,276	20.024	0.631
	– 2.97 to 1.43	157,432	38.609	41,979	41.458	1.074
	– 1.43 to 0.64	74,951	18.381	23,861	23.565	1.282
	0.64–3.58	33,695	8.264	10,523	10.392	1.258
	3.58–10.33	12,361	3.031	4618	4.561	1.504
Elevation (m)	194.53–437	6032	1.449	3	0.003	0.002
	113.71–194.53	18,463	4.434	6	0.006	0.001
	74.19–113.71	92,909	22.315	11	0.011	0.000
	47.25–74.19	168,402	40.447	7212	6.902	0.171
	21–47.25	130,544	31.354	97,260	93.079	2.969
Soil	Togo series	40,875	9.569	8899	8.286	0.866
	Tertially	48,469	11.347	5046	4.698	0.414
	Dahomeyan	80,320	18.803	6614	5.227	0.278
	Accraian	186,125	43.573	46,010	43.771	1.005
	Recent	71,372	16.708	40,830	38.017	2.275
Distance to road (m)	6033.04–9876.52	9836	2.533	67	0.070	0.028
	3621.44–6033.04	22,102	5.691	901	0.938	0.165
	2038.83–3621.44	51,748	13.325	12,120	12.624	0.947
	946.08–2038.83	111,092	28.605	29,550	30.779	1.076
	267.81–946.08	193,585	49.846	53,369	55.589	1.115
Sediment Transport Index (STI)	0–2.83	208,729	96.171	50,072	94.638	0.984
	2.83–12.24	6684	3.080	2018	3.814	1.238
	12.24–30.61	1208	0.557	532	1.006	1.807
	30.61–64.04	341	0.157	212	0.401	2.550
	64.04–120.08	77	0.035	75	0.142	3.996

forested area (0.39). LULC of an area is important to identify flood-prone areas in a river catchment. For instance, forest may act as natural resistance to flood prevention in an area. However, open fields and unprotected areas, such as water, crop and bare lands may be susceptible to flooding. Again, concretization in built-up areas results in an insignificant amount of groundwater percolation while aiding high surface runoff.

Concerning drainage density, areas with low drainage density have higher chances of flooding. For instance, areas with lower drainage density (< 27) in Greater Accra observed about 38% of historical flooding as FR values for subclasses between 0.001–13.3 and 13.3–26.99 were all above one (see Table 2). This reveals the susceptibility of these areas. Table 2 shows that areas between 0.036° and 1.23° slope subclass are prone to flooding as the FR value (1.26) is more than one. The slope of an area controls the occurrence of flooding, as low-lying areas have a significant relationship with flooding conditions in the rainy season. High numbers of flood events occur in lower slope regions as the water cannot discharge rapidly. Furthermore, curvature between – 1.04–0.04 and 0.04–1.02 produced FR values greater than 1. This shows that areas within these two classes are susceptible to flooding. Likewise, areas with Aspect between – 1 and 73.56 producing FR values greater than one.

The TWI and elevation are also important flood conditioning factors. Flood probability tends to increase where TWI increases. For instance, all the subclasses (except the first subclass) had FR values greater than one (see Table 2). However, flood probability increases when elevation decreases. Thus, FR values decrease when altitude increases and vice versa.

For instance, the FR value obtained for the lower elevated areas (21–47 m above sea level) recorded high FR value of 2.97. This reveals a significant impact of elevation on flood occurrence in the Greater Accra region. For soil, the Recent and Accranian soil types were found to influence the occurrence of flooding by producing FR values of 2.27 and 1 respectively. Moreover, Furthermore, the distance to a road between 267–946 m and 946–2038 m produced FR values of 1.12 and 1.08, respectively. This suggests that proximity to a road increases flood susceptibility in Greater Accra. Finally, all subclasses of STI, except the first subclass, produced FR values above one.

3.2 Mapping of flood susceptibility in Greater Accra

For preparing the flood-vulnerable maps, layers were created for all—15 flood conditioning factors and prediction rates estimated respectively. The prediction rate, which curbs issues of drawback and considers the mutual interrelationship among independent factors was estimated. The prediction rate reveals the sensitivity of individual flood conditioning factors with the training data. All the flood conditioning factors were combined for the baseline and future periods to generate flood susceptibility maps for the baseline period and under the SSP scenarios. For preparing the flood-vulnerable map for the baseline period, the results were categorized into 5 subclasses ranging from very low to very high. Figure 5 present the final flood susceptibility map. The prediction rate of flood conditioning factors (left) and percentage of flood vulnerable zones (right) are presented in Fig. 6. Elevation, slope, soil, distance from urban, and SPI were the first five most sensitive parameters that supported flooding in the Greater Accra region, with elevation being the most sensitive parameter (Fig. 6). About 37% of the total area of Greater Accra is categorized under the moderate

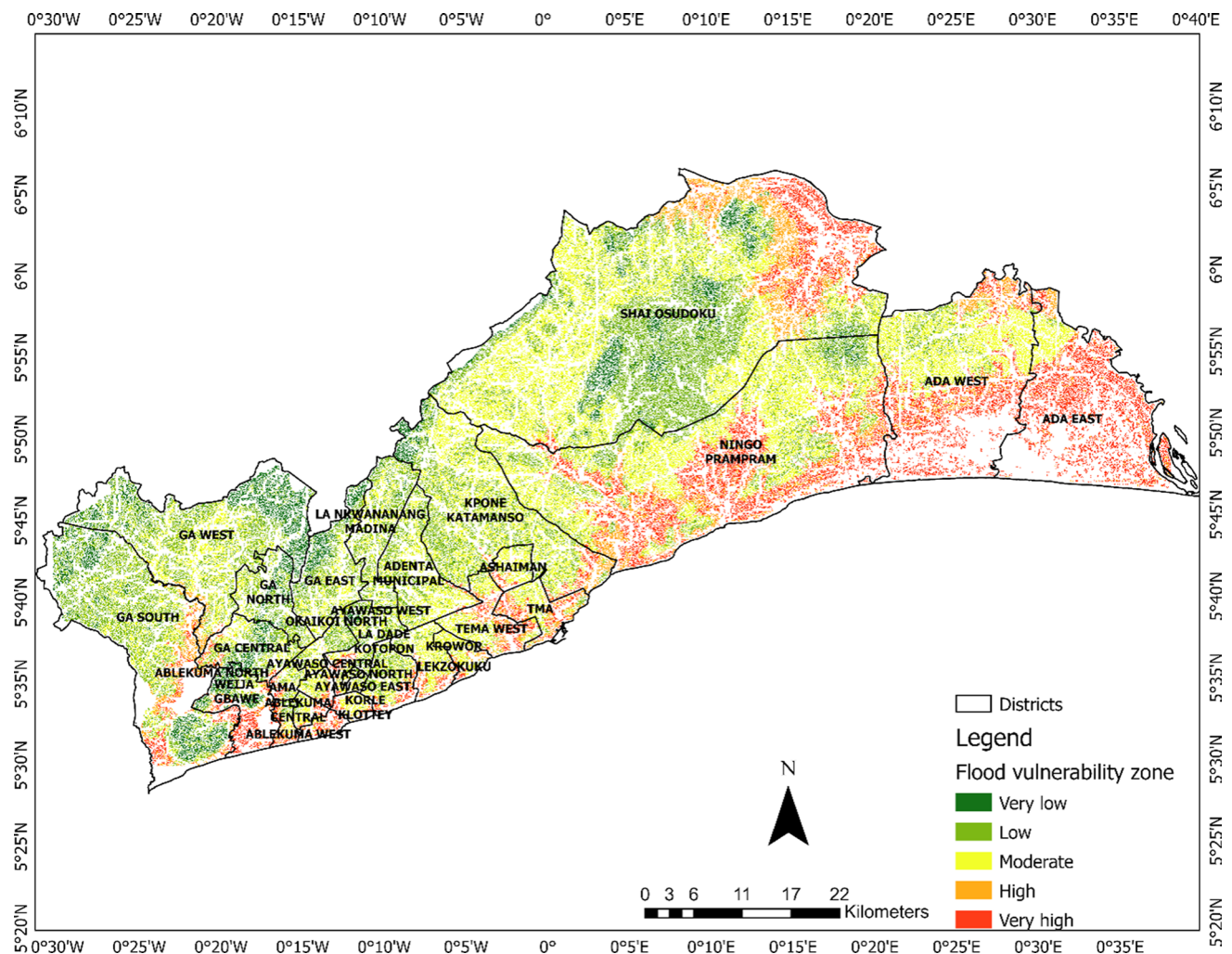


Fig. 5 Flood susceptibility map of Greater Accra region for the year 2020

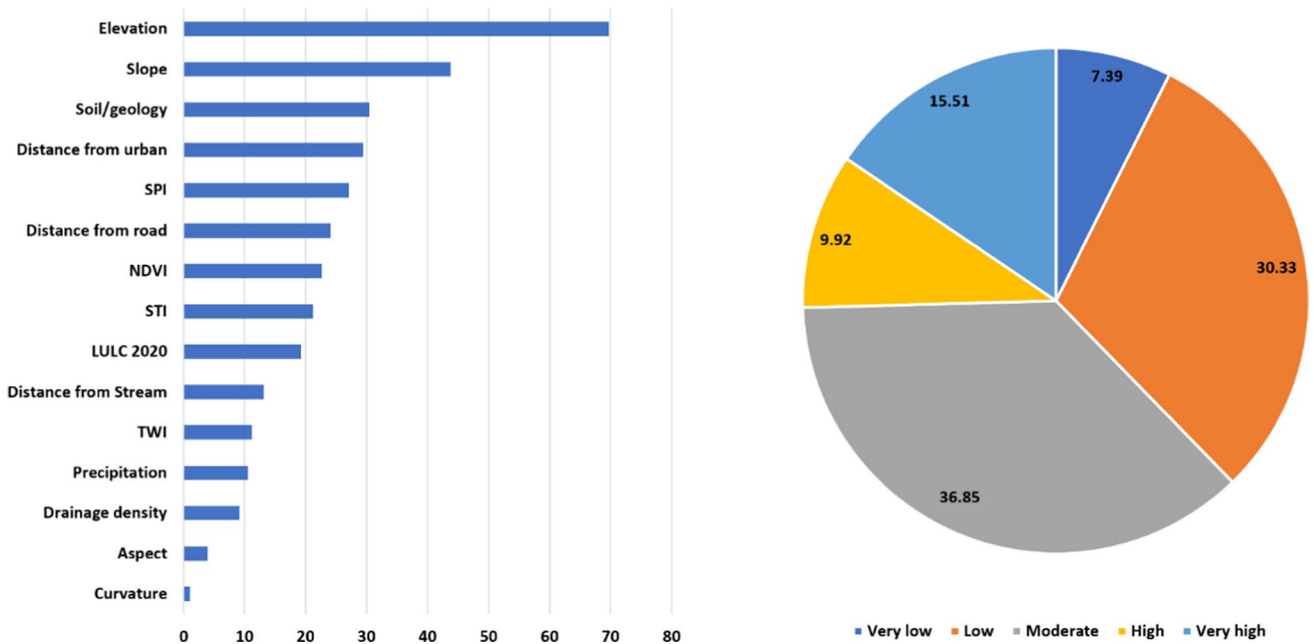


Fig. 6 Prediction rate of flood conditioning factors used in the FR model (left) and percentage of flood susceptibility zones (right)

flood-vulnerable zone category (Fig. 6, right). This followed by about 30% categorized under the low flood-vulnerable zone. However, about 15.5% was categorized under the very high flood-vulnerable zone (Fig. 6, right). Districts such as Ga South, Accra Metropolis, La Dade-Kotopon, Ledzokuku-Krowor, Kpone Katamanso, Ningo Prampram, Ada West and Ada East had parts located in the very high flood susceptibility zone (see Fig. 5). All these areas are very low-lying and along

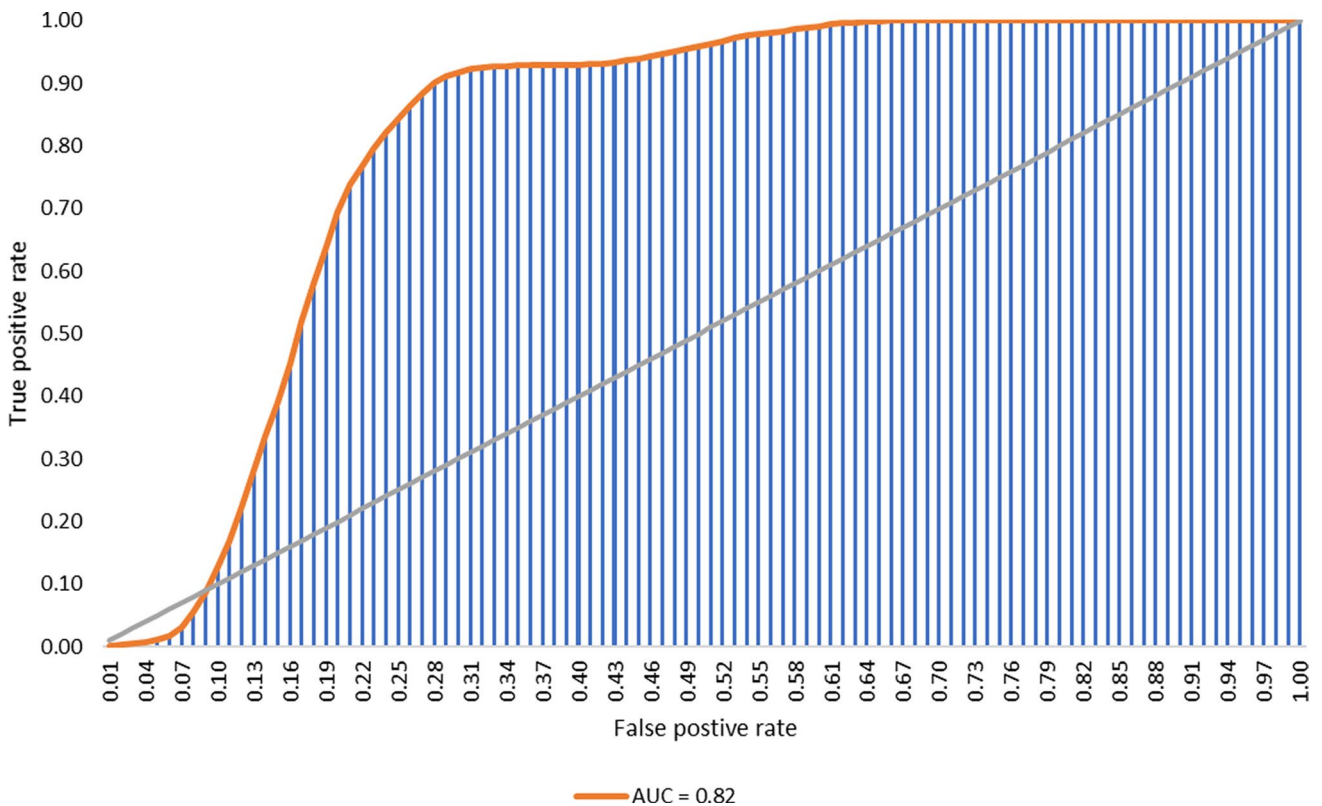


Fig. 7 ROC curve of the FR model

the coastal regions of Greater Accra (Fig. 5). This reveals the susceptibility of low-lying and coastal areas to flooding. The present study attained an AUC value of 0.83 (see Fig. 7), which shows that the model is very good and accurate for flood susceptibility mapping for Greater Accra. It also shows the usefulness of the FR model in flood susceptibility mapping.

3.3 Future flood susceptibility projections under the SSP scenarios

Figure 8 compares the flood susceptibility zones in the baseline in 2020 and SSP scenarios in 2055. Likewise the baseline, the coastal and low-lying areas are expected to be more vulnerable to flooding under all SSP scenarios (Fig. 8). However, the FSI differs across scenarios with intensification under the SSP2 and SSP3 (Fig. 8). For instance, Fig. 9 reveals a reduction in the low and moderate flood-susceptible zones under the SSP1 scenario compared to the baseline. The highest area expected to be covered by the moderate flood zone is about 33% under the SSP1 scenario compared to 37% in the baseline period. Also, very low flood-susceptible zones are expected to increase to about 14% of the total area compared to about 7% in the baseline. Generally, flood susceptibility is expected to be moderate under the SSP1 scenario (Fig. 9). However, very high susceptibility zones are expected to slightly increase under the SSP1 scenario compared to the baseline. Between 2020 and 2040 under SSP1, the primary drivers expected to influence flooding occurrence are elevation, slope, distance from urban areas, soil type, and SPI, as detailed in Appendix 1. Notably, by 2045, precipitation replaces SPI as the fifth parameter. Moreover, within the same scenario, precipitation subsequently supplants soil type/geology as the fourth parameter in 2050 and 2055, as indicated in Appendix 1. For the percentage change in flood susceptibility zones, the SSP 1 scenario is expected to observe increase in very low flood susceptibility areas (Fig. 10).

Flood susceptibility projections under the SSP2 scenario reveals similar trends as in SSP1, especially from 2020 to 2035 (see Fig. 10). However, the trend is expected to change from 2040 to 2055. For instance, moderate flood zones are expected to increase to about 41.3% and 43.7% in 2040 and 2045, respectively, compared to about 36.9% in the baseline (Fig. 9). In 2050 and 2055, the percentage of flood susceptibility zones is expected to move from moderate to high zones (about 29.4% and 30.5%, respectively). Again, very high flood susceptibility zones are expected to increase in 2050 (24.3%) and 2055 (25%). As such the SSP2 scenario is expected to observe an increase in high (19.4%) and very high (8.8%) in 2050 as well as an increase of 20.6% in high and very high (9.5%) flood susceptibility zones in 2055 (Fig. 10).

The flood susceptibility projections in the SSP3 scenario resembled those of the SSP2 scenario, showcasing a prevalence of moderate flood susceptibility from 2040 to 2045. Nevertheless, under the SSP3, there's an anticipated rise in

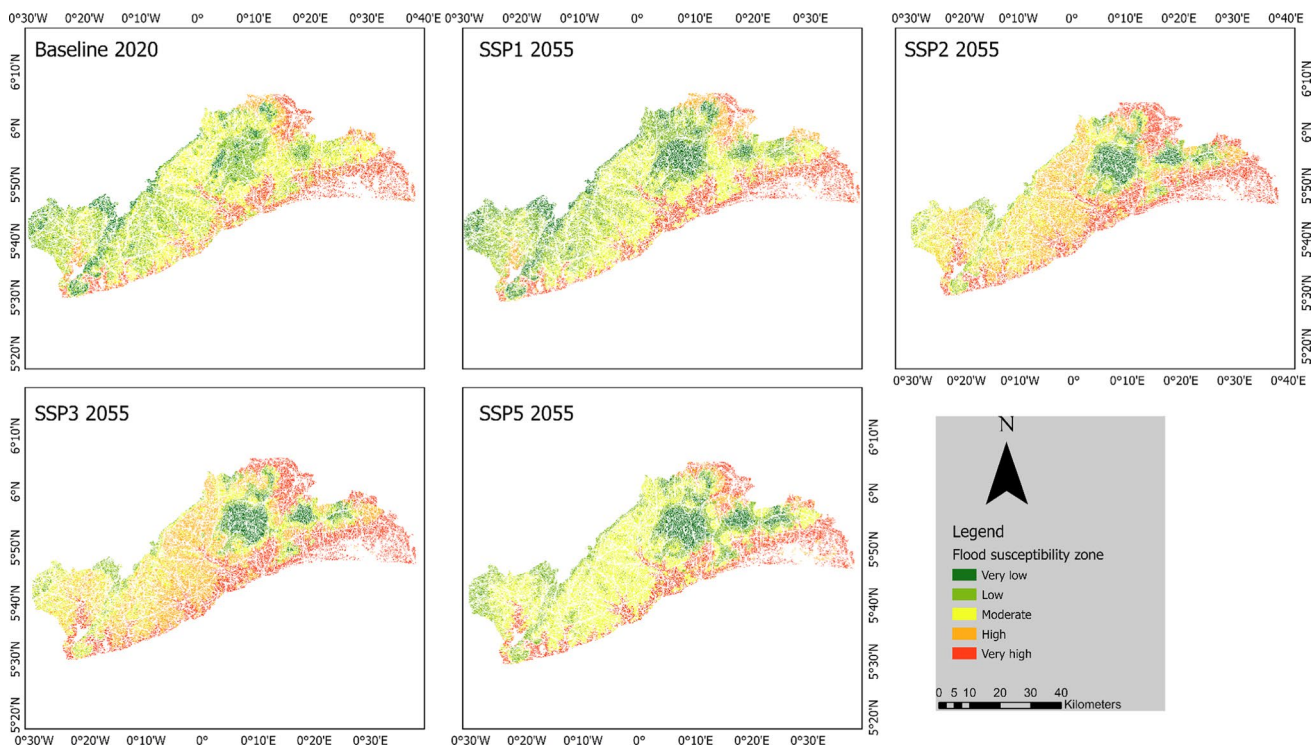


Fig. 8 Flood susceptibility zones under the SSP scenarios in 2055 relative to the baseline

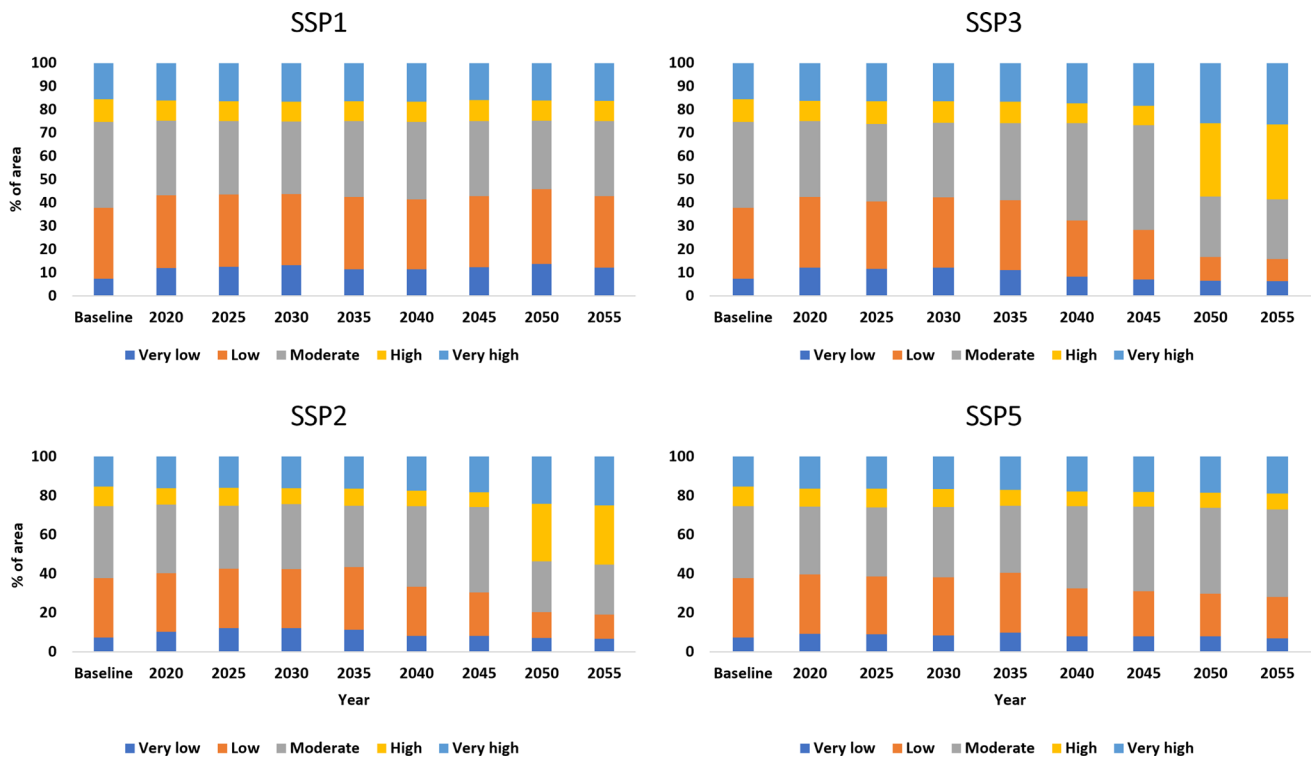


Fig. 9 Percentage of flood susceptibility zones under the SSP scenarios

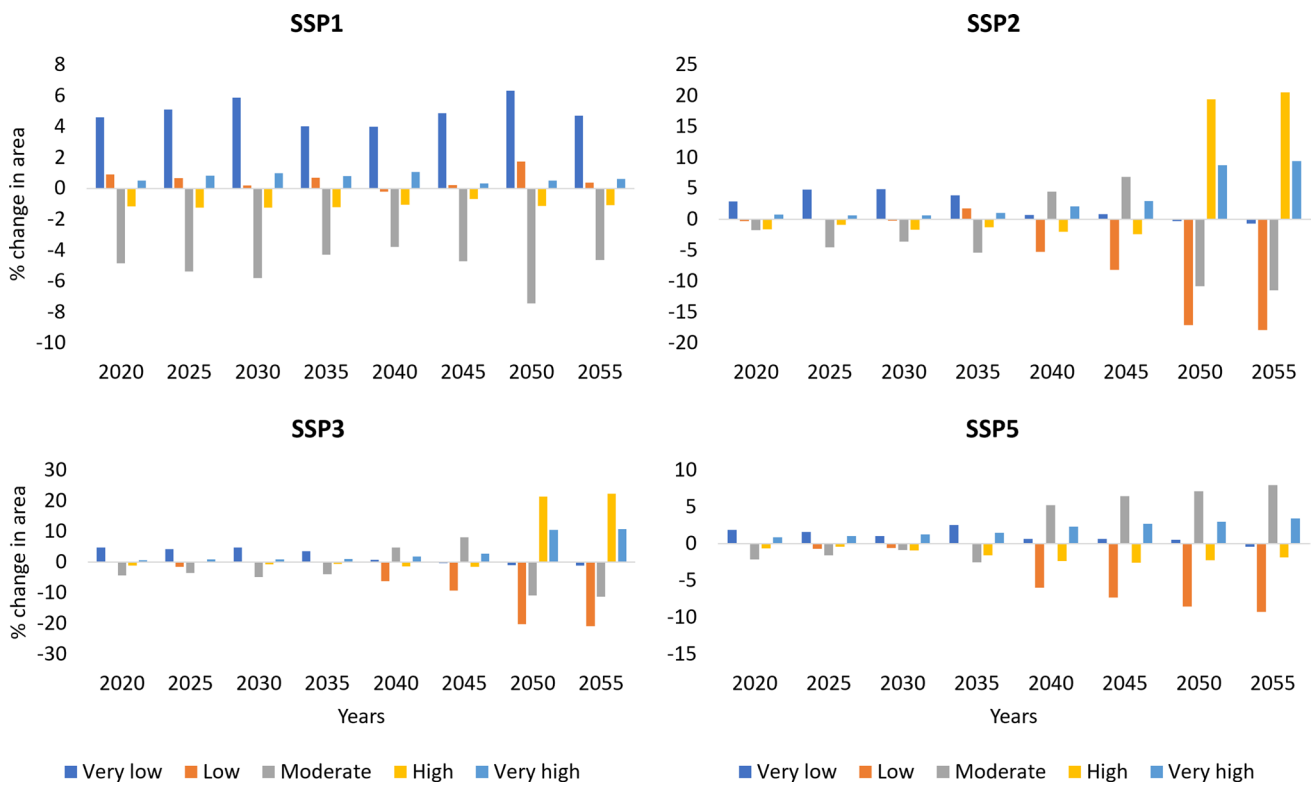


Fig. 10 Percentage change in flood susceptibility zones under the SSP scenarios relative to the baseline scenario

the extent of high and very high flood susceptibility zones compared to the SSP2. Specifically, the areas categorized as high and very high flood susceptibility zones are projected to expand to approximately 31.4% and 26% respectively by 2050, compared to the respective percentages of 29.4% and 24.3% under SSP2, and are expected to maintain similar increments by 2055 (Fig. 9). This is expected to cause an increase in very high flood susceptibility zones by about 21.5% and 22.3% in 2050 and 2055 respectively.

Elevation, slope, proximity to urban areas, soil type/geology, and SPI are anticipated to serve as the primary influential factors driving flooding occurrences within the SSP2 and SSP3 scenarios, as outlined in Appendix 1. However, the upward movement of distance from urban in the prediction rate, together with other drivers, shifted the dominant flood susceptibility index from moderate to high (see Appendix 1). This is evident in the 2055 of SSP2 and SSP3 where distance from urban became the second most significant flood conditioning factor (see Appendix 1).

For SSP5, flood susceptibility projections reveal a similar trend as SSP1 across all the years under study (see Fig. 10). However, the severity of flood susceptibility differs under the SSP5. Flood susceptibility is generally expected to be in the moderate flood susceptibility zone. However, the moderate flood susceptibility zones are expected to increase especially from 2040 to 2055 (see Fig. 10). For instance, the moderate flood susceptibility zones in 2050 and 2055 are expected to be about 44.41% and 44.47%, respectively, compared to 37% in the baseline year (Fig. 9). The primary influential factors include altitude, incline, proximity to urban areas, soil composition, and rainfall (Appendix 1). The SSP5 scenario is expected to observe increase in moderate and very high flood susceptibility zones especially from 2040 to 2055 (Fig. 10). See Appendix 2 for the spatio-temporal distribution of flood susceptibility zones under the SSPs in Greater Accra.

3.4 Flood duration

Figure 11 illustrates a clear trend of increasing flood duration hours in Accra across all modeled rainfall intensity scenarios and future years. Under the moderate flooding scenario, flood duration is projected to rise from a baseline of 320 h per year in 2020 to over 500 h in 2055. The increase is most pronounced in the high rainfall months of March to October. This reflects intensification of precipitation expected under climate change. The high and very high rainfall scenarios, representing more extreme events, show even greater flood duration increases. In the very high scenario, flooding is estimated to reach 640 h in 2045 and exceed 800 h in 2055—more than double the 2020 baseline. While flooding

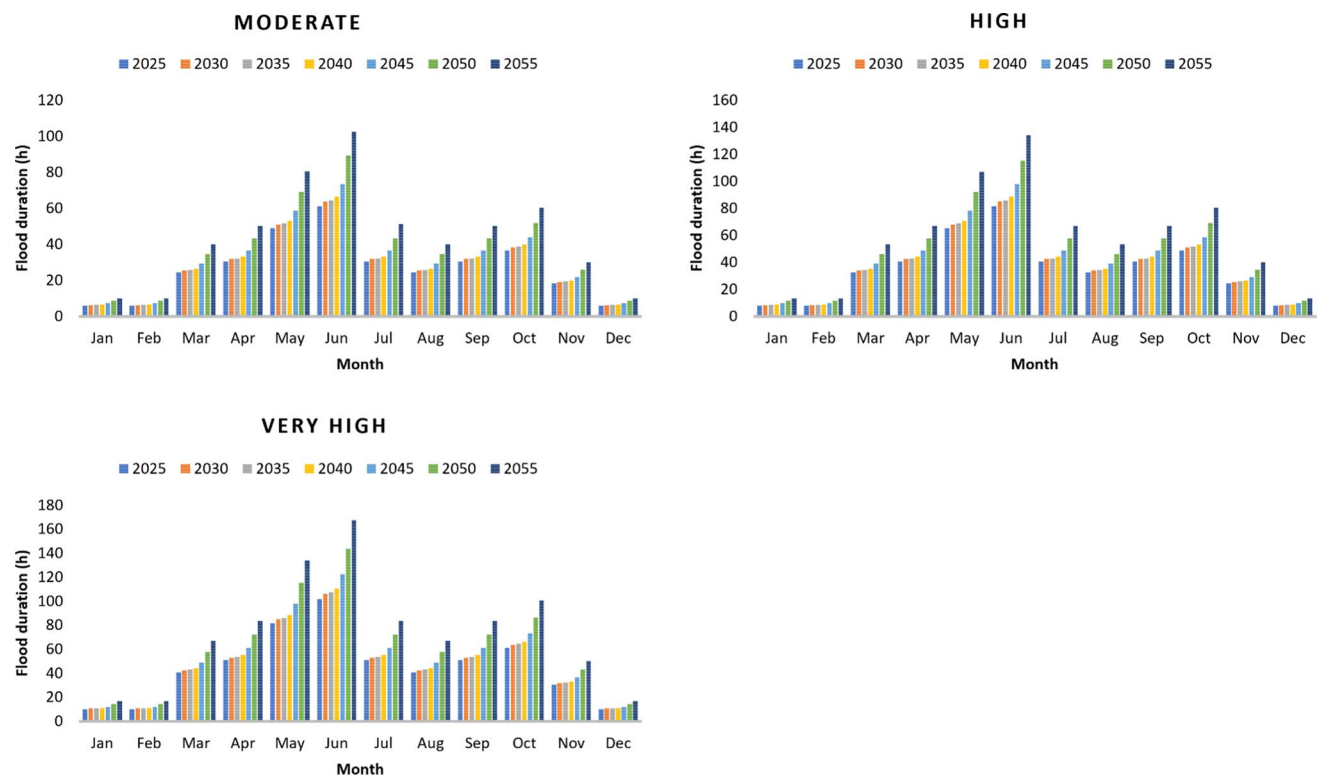


Fig. 11 Flooding duration for different intensity scenarios

remains higher in the rainy season, the analysis also highlights the risk of extreme rainfall events occurring in typically drier months. December 2055 could see very high rainfall flooding up to 17 h in the month. The results underscore the growing threat seasonal and extreme flooding poses to greater Accra across all rainfall scenarios. Adaptation efforts will need to consider both typical and maximum potential flood levels.

3.5 BSP flood risk assessment

The baseline flood susceptibility map in Fig. 12 depicts the locations of bulk supply points, which are labeled with station codes in alphabetical order and their localities. Figure 13 is a chart illustrating the flooding susceptibility of each station under different SSP scenarios. The susceptibility levels range from very low (green) to very high (red). The chart also provides estimates of potential electricity supply curtailed at each station. These estimates are based on the station capacities and duration of flooding and do not consider flood defense systems in the baseline scenario.

The analysis shows the bulk supply points face increasing flood susceptibility, with risks escalating most sharply under the severe climate change SSP3 and SSP5 scenarios. In the 2025–2035 period, over 75% of BSPs fall in the low- to medium-risk categories across SSPs. However, by 2055, more than 50% of BSPs are within medium- to high-risk categories in all scenarios except SSP1, reflecting the impact of climate change. SSP3 and SSP5 stand out with over 60% of BSPs facing high or very high flooding risks by 2055. Coastal and low-lying BSPs like Tema Siemens, Dawhenya, and Awoshie are most vulnerable, with thousands of megawatt-hours denied each year. Persistent failures at these facilities would cripple industrial zones and commercial areas. The results highlight the urgent need for flood resilience adaptation, as power assets currently lack protection. Without major infrastructure improvements, Accra faces severe electricity service disruptions from BSP failures due to flooding, jeopardizing critical facilities and economic functions. Early action under SSP1 to limit emissions and upgrade at-risk BSPs could avoid the worst impacts. However, delayed action under SSP3 and SSP5 could leave Accra’s power system highly susceptible to devastating floods. Proactive resilience investments will be essential to ensure BSP operability and energy security for Greater Accra’s growing population.

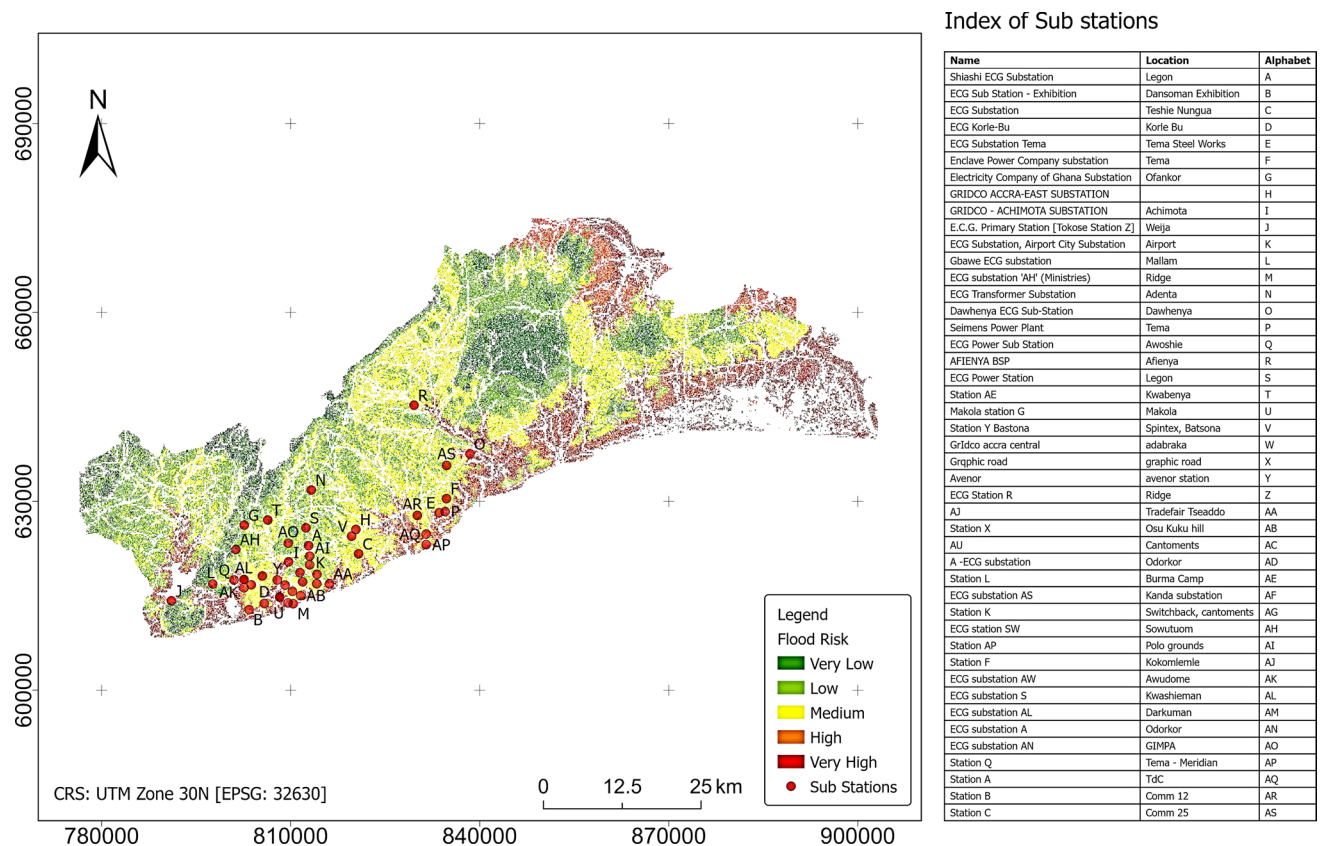


Fig. 12 2020 flood susceptibility map of the BSPs

BSP code	SSP1 (GWh)						SSP2 (GWh)						SSP3 (GWh)						SSP5 (GWh)									
	2025	2030	2035	2040	2045	2055	2025	2030	2035	2040	2045	2055	2025	2030	2035	2040	2045	2055	2025	2030	2035	2040	2045	2055				
A	0	0	0	3289	3636	4283	4980	3028	3152	3196	3289	3636	4283	6640	3028	3152	3196	3289	3636	5710	8300	0	0	0	0	3636	5710	4980
B	0	0	0	3289	3636	4283	4980	3028	3152	3196	3289	3636	4283	6640	3028	3152	3196	3289	3636	5710	8300	3028	3152	3196	3289	3636	5710	4980
C	0	0	0	3289	3636	4283	4980	3028	3152	3196	3289	3636	4283	6640	3028	3152	3196	3289	3636	5710	8300	3028	3152	3196	3289	3636	5710	6640
D	0	0	0	3289	3636	4283	4980	3028	3152	3196	3289	3636	4283	6640	3028	3152	3196	3289	4849	5710	8300	3028	3152	3196	3289	3636	5710	6640
E	0	0	0	0	3636	4283	4980	3028	3152	3196	3289	3636	4283	6640	3028	3152	3196	3289	4849	5710	8300	0	0	0	0	3636	5710	6640
F	3028	3152	3196	3289	3636	4283	4980	3028	3152	3196	3289	3636	4283	6640	3028	3152	3196	3289	4849	5710	8300	3028	3152	3196	3289	3636	5710	4980
G	0	0	0	0	0	0	0	0	0	3196	3289	3636	4283	4980	3028	3152	3196	3289	3636	4283	6640	0	0	0	0	3636	0	0
H	3028	3152	3196	3289	3636	4283	6640	3028	3152	3196	3289	3636	4283	6640	3028	3152	3196	3289	3636	5710	6640	3028	3152	3196	3289	3636	5710	6640
I	5047	5254	5327	5481	6061	7138	8300	5047	5254	5327	5481	6061	7138	8300	4038	5254	5327	5481	6061	7138	8300	5047	5254	5327	5481	6061	7138	8300
J	4038	4203	5327	4385	6061	5710	6640	4038	5254	5327	5481	6061	7138	8300	4038	5254	5327	5481	6061	7138	8300	4038	5254	5327	5481	6061	5710	6640
K	0	0	0	0	3636	0	0	0	0	3196	3289	3636	4283	4980	0	0	3196	3289	3636	4283	4980	0	0	0	0	3636	0	0
L	3028	3152	0	0	0	0	6640	3028	3152	3196	3289	3636	4283	6640	3028	3152	3196	3289	3636	5710	8300	0	3152	0	0	3636	0	6640
M	5047	5254	5327	5481	6061	7138	8300	5047	5254	5327	5481	6061	7138	8300	5047	5254	5327	5481	6061	7138	8300	5047	5254	5327	5481	6061	7138	8300
N	0	3152	3196	3289	0	4283	4980	3028	0	3196	3289	3636	4283	4980	3028	3152	3196	3289	3636	4283	4980	0	0	0	0	0	4283	4980
O	5047	5254	5327	5481	6061	7138	8300	5047	5254	5327	5481	6061	7138	8300	5047	5254	5327	5481	6061	7138	8300	5047	5254	5327	5481	6061	7138	8300
P	5047	5254	5327	5481	6061	7138	8300	5047	5254	5327	5481	6061	7138	8300	5047	5254	5327	5481	6061	7138	8300	5047	5254	5327	5481	6061	7138	8300
Q	5047	5254	5327	5481	6061	7138	8300	5047	5254	5327	5481	6061	7138	8300	5047	5254	5327	5481	6061	7138	8300	5047	5254	5327	5481	6061	7138	8300
R	0	3152	0	3289	3636	4283	6640	3028	3152	3196	3289	3636	4283	6640	3028	3152	3196	3289	3636	5710	6640	3028	3152	3196	3289	3636	4283	6640
S	0	0	0	0	0	0	4980	0	0	3196	3289	3636	4283	4980	0	3152	3196	3289	3636	4283	6640	0	0	0	0	3289	0	4980
T	0	0	0	0	0	0	4980	0	0	3196	3289	3636	4283	4980	0	3152	3196	3289	3636	4283	6640	0	0	0	0	3289	0	4980
U	4038	5254	5327	5481	6061	7138	8300	5047	5254	4262	5481	6061	7138	8300	5047	5254	5327	5481	6061	7138	8300	5047	5254	5327	5481	6061	7138	8300
V	3028	3152	3196	3289	3636	4283	6640	3028	3152	3196	3289	3636	4283	6640	3028	3152	3196	3289	3636	5710	6640	3028	3152	3196	3289	3636	4283	6640
W	5047	5254	4262	5481	6061	7138	8300	5047	5254	5327	5481	6061	7138	8300	5047	5254	5327	5481	6061	7138	8300	5047	5254	5327	5481	6061	7138	8300
X	5047	5254	4262	5481	6061	7138	8300	5047	5254	5327	5481	6061	7138	8300	5047	5254	5327	5481	6061	7138	8300	5047	5254	5327	5481	6061	7138	8300
Y	4038	4203	4262	4385	6061	5710	8300	4038	4203	4262	5481	4849	5710	8300	4038	4203	4262	5481	4849	7138	8300	4038	4203	4262	5481	6061	5710	8300
Z	3028	3152	3196	3289	3636	4283	6640	3028	3152	3196	3289	3636	5710	8300	3028	3152	3196	3289	3636	5710	6640	3028	3152	3196	3289	3636	4283	6640
AA	5047	5254	5327	5481	6061	7138	8300	5047	5254	5327	5481	6061	7138	8300	5047	5254	5327	5481	6061	7138	8300	5047	5254	5327	5481	6061	7138	8300
AB	0	0	0	3289	3636	4283	6640	3028	3152	0	3289	3636	4283	4980	3028	3152	3196	3289	3636	5710	6640	3028	3152	3196	3289	3636	4283	6640
AC	3028	3152	3196	3289	3636	4283	6640	3028	3152	3196	3289	3636	4283	6640	3028	3152	3196	3289	3636	5710	6640	3028	3152	3196	3289	3636	4283	6640
AD	3028	3152	3196	3289	3636	4283	6640	3028	3152	3196	3289	3636	4283	6640	3028	3152	3196	3289	3636	5710	6640	3028	3152	3196	3289	3636	4283	6640
AE	3028	3152	3196	3289	3636	4283	6640	0	3152	0	3289	3636	4283	6640	3028	3152	3196	3289	3636	5710	6640	3028	3152	3196	3289	3636	4283	6640
AF	3028	0	3196	3289	3636	0	4980	0	0	0	3289	3636	4283	6640	3028	0	0	3289	0	4283	4980	0	0	0	3289	3636	0	4980
AG	3028	3152	3196	3289	3636	4283	6640	3028	3152	3196	3289	3636	5710	8300	3028	3152	3196	3289	3636	5710	6640	3028	3152	3196	3289	3636	4283	6640
AH	0	0	0	0	0	0	4980	0	0	0	0	0	0	4980	0	0	0	0	3289	3636	4283	4980	0	0	0	0	0	4980
AI	3028	3152	3196	3289	3636	4283	4980	0	3152	3196	3289	3636	5710	6640	3028	3152	0	3289	4849	5710	6640	3028	3152	3196	3289	3636	4283	4980
AJ	5047	5254	5327	5481	6061	7138	8300	5047	5254	5327	5481	6061	7138	8300	5047	5254	5327	5481	6061	7138	8300	5047	5254	5327	5481	6061	7138	8300
AK	3028	3152	3196	3289	3636	4283	6640	3028	3152	0	3289	3636	4283	6640	3028	3152	3196	3289	3636	5710	6640	3028	3152	3196	3289	3636	4283	6640
AL	3028	3152	3196	3289	3636	4283	6640	3028	3152	0	3289	3636	4283	6640	3028	3152	3196	3289	3636	5710	6640	3028	3152	3196	3289	3636	4283	6640
AM	0	0	0	0	3636	0	6640	0	0	0	3289	3636	4283	6640	0	0	0	3289	3636	4283	4980	0	0	0	3289	3636	0	6640
AN	3028	3152	3196	3289	3636	4283	6640	3028	3152	0	3289	3636	5710	6640	3028	3152	3196	3289	3636	5710	6640	3028	3152	3196	3289	3636	4283	6640
AO	3028	3152	3196	3289	3636	4283	6640	3028	3152	0	3289	3636	5710	6640	3028	3152	3196	3289	3636	4283	6640	3028	3152	3196	3289	3636	4283	6640
AP	0	0	0	0	3636	5710	6640	3028	3152	3196	3289	3636	5710	6640	5047	4203	4262	4385	4849	5710	6640	0	4203	4262	4385	3636	5710	6640
AQ	3028	3152	0	0	3636	4283	4980	3028	3152	3196	3289	3636	5710	6640	3028	0	0	3289	3636	5710	6640	3028	0	0	3289	3636	4283	4980
AR	3028	3152	3196	3289	3636	4283	4980	3028	3152	3196	3289	3636	5710	6640	3028	3152	3196	3289	3636	5710	6640	3028	3152	3196	3289	3636	4283	4980
AS	3028	3152	3196	0	3636	4283	4980	3028	3152	3196	3289	3636	5710	6640	3028	3152	3196	3289	3636	5710	6640	0	0	0	3289	3636	4283	4980

Fig. 13 BSP flood susceptibilities and power denied across SSP scenarios

3.6 Power curtailed due to flooding

The flood risk analysis shows power denied due to outages escalating over time, but with distinct trends across scenarios as shown in Fig. 14. SSP1 sees the smallest increases, rising from 112 GWh in 2025 to 279 GWh in 2055—a 4.2% of the total electricity supply of 3685.77 GWh annually for the BSPs considered. SSP2 and SSP3 follow similar growth trajectories, reaching over 300 GWh and 5% supply loss by 2055. However, SSP5 denial remains the second lowest, peaking at 284 GWh (4.4%) in 2055. The results indicate that persistent losses of this magnitude would require load shedding and blackouts during major flood events. Even SSP1, the best case climate change and socioeconomic development scenario, could see significant local outages from flooded BSPs. There is the need to target adaptation investments at vulnerable BSPs. Protecting or relocating a few high-risk facilities could maintain electricity access for most customers, even if flooding increases.

4 Discussion

4.1 Flood projections under the SSP scenarios in the Greater Accra region

The results of the study show high positive correlation between the flood conditioning factors and the occurrence of flooding in the Greater Accra region as revealed by the FR values. Elevation, distance from urban, slope, soil, SPI and precipitation were the first five most

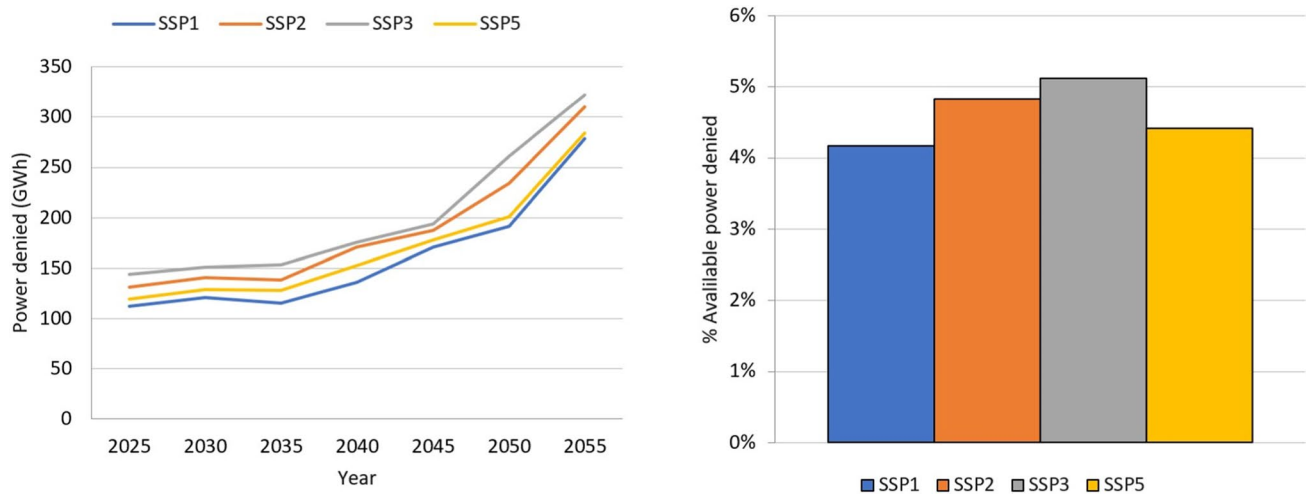


Fig. 14 Electricity denied forecast (left) and percentage of electricity denied from total BSP supply (right)

Greater Accra region, with SPI and precipitation interchanging positions under the SSP scenarios. Several studies have attributed flooding in Greater Accra to non-meteorological factors [70]. For instance, elevation was generally found to be the most sensitive flood condition factor in the Greater Accra region as areas between 21 and 47.25 m above sea level (especially areas along the coastal line) were found to be highly vulnerable in the historical and future periods. The study of Ansah et al. [70] revealed that Accra is a coastal region at low altitude that receives run-offs from high altitude, especially in the month of June, which is the peak of the major rainy season over southern Ghana. Consecutive wet days over inland areas and high grounds continually drained off to the sea. Due to the low-lying nature of the Greater Accra region, the run-offs accumulate, resulting in stray waters entering urban and unprotected areas. While elevation may not fall under meteorological flood conditioning factors, it remains a significant natural element in flood occurrence. Given the challenging nature of addressing natural factors, adaptation strategies need to carefully account for additional factors, such as proximity to urban areas, for effective flood management in the region.

Again, distance from urban areas is the second-most sensitive flood conditioning factor in the Greater Accra region, especially in the future under the SSP scenarios. The SSP2 and SSP3 scenarios are expected to be the worst-case scenarios where high flood susceptibility zones are expected to generally dominate. This may be attributed to the population projections under the SSP2 and SSP3 scenarios. For instance, population is expected to hit 9 and 12.6 billion by the end of the twenty-first century [72]. These increases are expected to affect urban growth since population and urbanization have a proportional relationship. Therefore, as population increases, urbanization is expected to also increase, which provides conditions conducive to flooding, especially in an already densely populated region like in Greater Accra. As a result, distance from urban was found to have great influence on the occurrence of flooding in the Greater Accra region, especially from 2040 to 2055 under SSP2 and SSP3. The proliferation of hardscapes, unplanned settlements in flood-prone areas, poor drainage systems, limited tree planting, limited roof-top rain harvesting systems, and unplanned settlements and settlements in riparian zones and wetlands, coupled with the high generation of solid waste which ends up in drains other areas are associated with urban sprawl, which leads to increased run-off in these areas [1, 19, 70, 73]. As a result, even moderate precipitation can trigger floods, posing a significant challenge for city planners, particularly regarding the management of infrastructural development in the area [70]. The sensitivity of the flood conditioning factors, such as slope, soil type and SPI, persisted consistently across all the SSP scenarios in the Greater Accra region. However, precipitation as a meteorological flood conditioning factor was amongst the top flood conditioning factors under the SSP1 and SSP5 scenarios. Soil type or geology was identified as one of the most influential factors contributing to flood occurrence in the region. Studies indicated that areas within the Accra metropolis characterized by Accranian and Togo series rock types experienced more frequent high floods. Geological formations prevalent in the Dahomeyan series were observed to channel runoff toward low-lying areas, thereby exacerbating flooding in the region, particularly within the Accra metropolis [45].

4.2 Flood resilience measures

The results show Accra's power system should increase adaptation measures to manage future supply impacts due to flooding as persistent flooding of these facilities would paralyze southern Accra's power supply chain. Key industrial and commercial areas could face prolonged blackouts during flood events, and hospitals, water services, and other critical infrastructure would be jeopardized.

To enhance resilience, flood defenses should be prioritized at the most vulnerable BSPs, like Achimota, Weija, Ridge, Dawhenya, Tema, Awoshie, Afienya, Spintex, Adabraka, Avenor, Tseaddo, Kokomlemle, and and Graphic Road substations. Elevating or relocating flood-prone components like transformers could enable them to function during lower-level flooding events [74]. Construction of berms, floodwalls, and raised access roads would shield facilities from extreme flooding. This approach has been explored in the context of flood prevention devices for transformer substations, where a baffle made of metal material is used to control floodwaters and prevent them from entering the substation [75]. Additionally, the concept of flexible transformers has been proposed, which can be used as replacements for different voltage levels and have adjustable impedance features to match the requirements of impacted substations [76, 77]. These flexible transformers have been proven to be functional and stable in both factory lab and field tests [78]. Furthermore, the use of flood monitoring systems with float switches which allows operators to de-energize equipment or substations prior to loss of control and eventual damage can be used as an early warning system [75]. In constructing new BSPs in high-risk zones should be avoided. Where relocation is infeasible, redundant connections and distributed supply sources, such as solar photovoltaic power with battery storage, could maintain power when legacy assets are flooded. Corrosion-resistant or galvanized substation equipment, such as bracing, purlins, and exterior panels can also be used where relocation is impractical [79]. By implementing these strategies, the impact of flooding on transformer substations can be reduced, ensuring a more reliable energy supply.

5 Conclusion

This study analyzed current and future flood risks and their impacts on electricity bulk supply points in Greater Accra, Ghana under different climate change (Shared Socioeconomic Pathway) scenarios. The study used 16 flood conditioning factors in simulating current and future flood conditions under the SSP scenarios using the Frequency Ratio (FR) model. The performance of the model was evaluated using the Receiver Operating Characteristic (ROC) curve, displaying high accuracy (an Area under the curve (AUC) value of 0.83) for flood susceptibility mapping in Greater Accra. Analysis reveals elevation, distance from urban areas, slope, soil type, SPI, and precipitation as the primary influential parameters increasing flood susceptibility in the region. Notably, elevation emerges as a critical factor, especially for areas near the coast between 21 and 47.25 m above sea level. Moreover, the distance from urban areas, particularly under SSP2 and SSP3 scenarios, emerges as another significant factor affecting flooding due to population growth and subsequent urbanization. Moreover, the study identified vulnerable electricity infrastructure and projected potential impacts on power supply for the region under the SSP scenarios. The results illustrate the urgent need to adapt Accra's power system infrastructure to increasing flood hazards driven by climate change. Electricity disruption due to flooding is projected to grow, leaving coastal and low-lying bulk supply points at high risk. Persistent flooding of these facilities would cripple Accra's electricity supply chain, jeopardizing key services and economic functions. To enhance resilience, the study recommends prioritizing upgrades like flood barriers, elevated equipment, and infrastructure hardening at the highest-risk bulk supply points. Restricting new development in floodplains is also critical to limit exposure. Collaborative adaptation efforts between utilities, government agencies, and communities will be essential to develop tailored resilience strategies. Model coupling with long-term energy system optimization models will also reveal optimal energy planning pathways to mitigate flooding impacts in the future, as part of further studies.

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Supervision. K.A.: Writing – review & editing, Supervision. G.K.A.: Writing – review & editing, Supervision. E.A.A.: Writing – review & editing. F.K.: Writing – review & editing, Supervision. M.Y.: Supervision, Writing – review & editing, Writing – original draft.

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Data availability The flood risk maps that supports findings of this study have been deposited in Zenodo with DOI: <https://zenodo.org/doi/https://doi.org/10.5281/zenodo.10631311>.

Declarations

Competing interests The authors declare no competing interests.

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Appendix 1: Prediction rates of flood conditioning factors

2020		2025		2030		2035		2040		2045		2050		2055	
Fac-tors	Predic-tion rate	Fac-tors	Predic-tion rate	Fac-tors	Predic-tion rate	Fac-tors	Predic-tion rate	Fac-tors	Predic-tion rate	Fac-tors	Predic-tion rate	Fac-tors	Predic-tion rate	Fac-tors	Predic-tion rate
SSP1															
1	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1	1.000
2	3.975	2	3.975	2	3.975	2	3.975	2	3.975	2	3.975	2	3.975	2	3.975
3	9.158	3	9.158	3	9.158	3	9.158	3	9.158	3	9.158	3	9.158	3	9.158
4	11.211	4	11.211	4	11.211	4	11.211	4	11.211	4	11.211	4	11.211	4	11.211
5	11.355	5	11.355	5	11.355	5	11.355	5	11.355	5	11.355	5	11.355	5	11.355
6	18.283	7	19.773	7	19.738	6	18.676	7	19.171	7	17.743	7	16.668	7	15.487
7	19.630	6	19.988	8	21.024	7	20.168	6	20.773	8	21.024	8	21.024	8	21.024
8	21.024	8	21.024	6	22.291	8	21.024	8	21.024	9	22.674	9	22.674	9	22.674
9	22.674	9	22.674	9	22.674	9	22.674	9	22.674	10	24.830	10	24.830	10	24.830
10	24.830	10	24.830	10	24.830	10	24.830	10	24.830	11	27.108	11	27.108	11	27.108
11	27.108	11	27.108	11	27.108	11	27.108	11	27.108	6	29.182	12	29.552	12	29.552
12	29.552	12	29.552	12	29.552	12	29.552	12	29.552	12	29.552	6	36.855	6	35.850
13	37.987	13	38.021	13	38.058	13	38.469	13	38.919	13	39.768	13	40.526	13	41.185
14	43.760	14	43.760	14	43.760	14	43.760	14	43.760	14	43.760	14	43.760	14	43.760
15	69.800	15	69.800	15	69.800	15	69.800	15	69.800	15	69.800	15	69.800	15	69.800
SSP2															
1	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1	1.000
2	3.975	2	3.975	2	3.975	2	3.975	2	3.975	2	3.975	2	3.975	2	3.975
3	9.158	3	9.158	3	9.158	3	9.158	3	9.158	3	9.158	3	9.158	3	9.158
4	11.211	4	11.211	4	11.211	4	11.211	4	11.211	4	11.211	4	11.211	4	11.211
5	11.355	5	11.355	5	11.355	5	11.355	5	11.355	5	11.355	5	11.355	5	11.355
6	18.794	7	19.665	6	18.168	7	18.574	6	15.515	7	16.058	7	14.308	7	13.239
7	21.024	8	21.024	7	18.795	6	20.518	7	17.508	6	20.816	6	17.041	6	21.001
8	22.674	9	22.674	8	21.024	8	21.024	8	21.024	8	21.024	8	21.024	8	21.024
9	24.047	6	23.138	9	22.674	9	22.674	9	22.674	9	22.674	9	22.674	9	22.674

2020		2025		2030		2035		2040		2045		2050		2055	
Fac-tors	Predic-tion rate	Fac-tors	Predic-tion rate	Fac-tors	Predic-tion rate	Fac-tors	Predic-tion rate	Fac-tors	Predic-tion rate	Fac-tors	Predic-tion rate	Fac-tors	Predic-tion rate	Fac-tors	Predic-tion rate
10	24.830	10	24.830	10	24.830	10	24.830	10	24.830	10	24.830	10	24.830	10	24.830
11	27.108	11	27.108	11	27.108	11	27.108	11	27.108	11	27.108	11	27.108	11	27.108
12	29.552	12	29.552	12	29.552	12	29.552	12	29.552	12	29.552	12	29.552	12	29.552
13	38.435	13	38.010	13	38.320	13	39.111	13	40.049	13	41.221	13	43.052	13	43.760
14	43.760	14	43.760	14	43.760	14	43.760	14	43.760	14	43.760	14	43.760	14	44.714
15	69.800	15	69.800	15	69.800	15	69.800	15	69.800	15	69.800	15	69.800	15	69.800
SSP3															
1	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1	1.000
2	3.975	2	3.975	2	3.975	2	3.975	2	3.975	2	3.975	2	3.975	2	3.975
3	9.158	3	9.158	3	9.158	3	9.158	3	9.158	3	9.158	3	9.158	3	9.158
4	11.211	4	11.211	4	11.211	4	11.211	4	11.211	4	11.211	4	11.211	4	11.211
5	11.355	5	11.355	5	11.355	5	11.355	5	11.355	5	11.355	5	11.355	5	11.355
6	18.536	7	19.722	6	15.515	7	19.029	7	16.786	7	17.312	7	14.104	7	12.966
7	18.813	8	21.024	7	19.728	8	21.024	6	17.646	8	21.024	8	21.024	8	21.024
8	21.024	6	21.845	8	21.024	9	22.674	8	21.024	9	22.674	9	22.674	6	21.936
9	22.674	9	22.674	9	22.674	6	24.668	9	22.674	10	24.830	6	22.995	9	22.674
10	24.830	10	24.830	10	24.830	10	24.830	10	24.830	6	25.926	10	24.830	10	24.830
11	27.108	11	27.108	11	27.108	11	27.108	11	27.108	11	27.108	11	27.108	11	27.108
12	29.552	12	29.552	12	29.552	12	29.552	12	29.552	12	29.552	12	29.552	12	29.552
13	38.964	13	38.004	13	37.966	13	38.518	13	39.128	13	40.026	13	42.983	14	43.760
14	43.760	14	43.760	14	43.760	14	43.760	14	43.760	14	43.760	14	43.760	13	44.552
15	69.800	15	69.800	15	69.800	15	69.800	15	69.800	15	69.800	15	69.800	15	69.800
SSP5															
1	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1	1.000
2	3.975	2	3.975	2	3.975	2	3.975	2	3.975	2	3.975	2	3.975	2	3.975
3	9.158	3	9.158	3	9.158	3	9.158	3	9.158	3	9.158	3	9.158	3	9.158
4	11.211	4	11.211	4	11.211	4	11.211	4	11.211	4	11.211	4	11.211	4	11.211
5	11.355	5	11.355	5	11.355	5	11.355	5	11.355	5	11.355	5	11.355	5	11.355
6	17.586	7	19.610	7	19.526	7	18.812	7	18.649	7	17.427	7	16.597	7	15.631
7	17.816	8	21.024	8	21.024	8	21.024	8	21.024	8	21.024	8	21.024	8	21.024
8	21.024	9	22.674	9	22.674	9	22.674	9	22.674	9	22.674	6	21.485	9	22.674
9	22.674	10	24.830	10	24.830	10	24.830	10	24.830	10	24.830	9	22.674	6	24.654
10	24.830	11	27.108	11	27.108	11	27.108	11	27.108	11	27.108	10	24.830	10	24.830
11	27.108	6	27.957	12	29.552	12	29.552	6	29.273	6	28.728	11	27.108	11	27.108
12	29.552	12	29.552	6	36.438	6	32.997	12	29.552	12	29.552	12	29.552	12	29.552
13	39.810	13	38.019	13	38.083	13	38.513	13	38.957	13	39.812	13	40.554	13	41.294
14	43.760	14	43.760	14	43.760	14	43.760	14	43.760	14	43.760	14	43.760	14	43.760
15	69.800	15	69.800	15	69.800	15	69.800	15	69.800	15	69.800	15	69.800	15	69.800

Factors: Curvature= 1, Aspect=2, Drainage density=3, TWI=4, Distance from stream=5, Precipitation for the respective year=6, LULC for the respective year=7, STI=8, NDVI=9, Distance to road=10, SPI=11, soil/geology=12, Distance from urban for the respective year=13, slope=14, Elevation=15.

Appendix 2: Flood vulnerability maps

See Figs. 15, 16, 17 and 18.

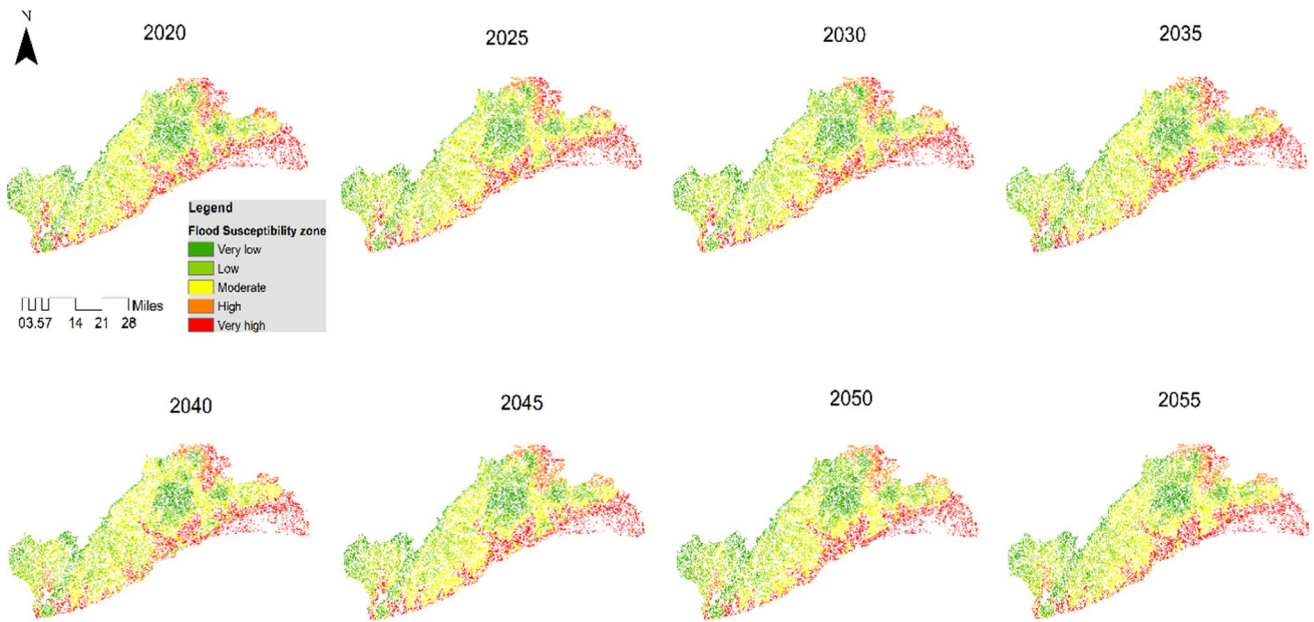


Fig. 15 Spatio-temporal distribution of flood vulnerability zones under the SSP1 scenario

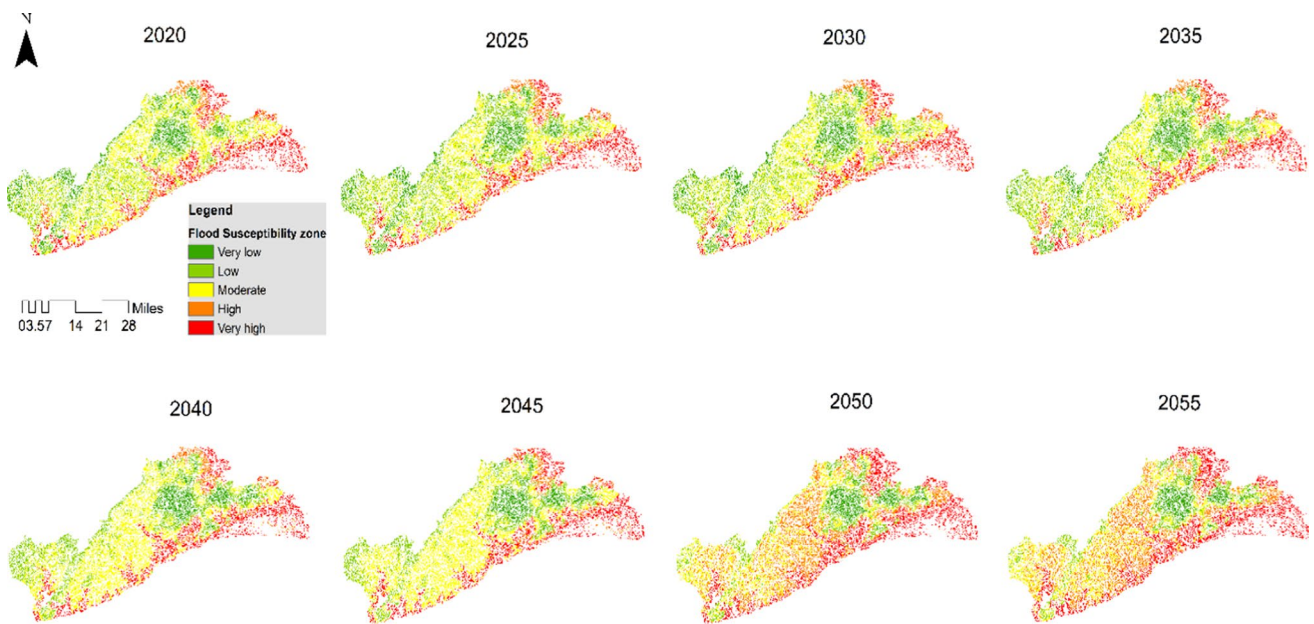


Fig. 16 Spatio-temporal distribution of flood vulnerability zones under the SSP2 scenario

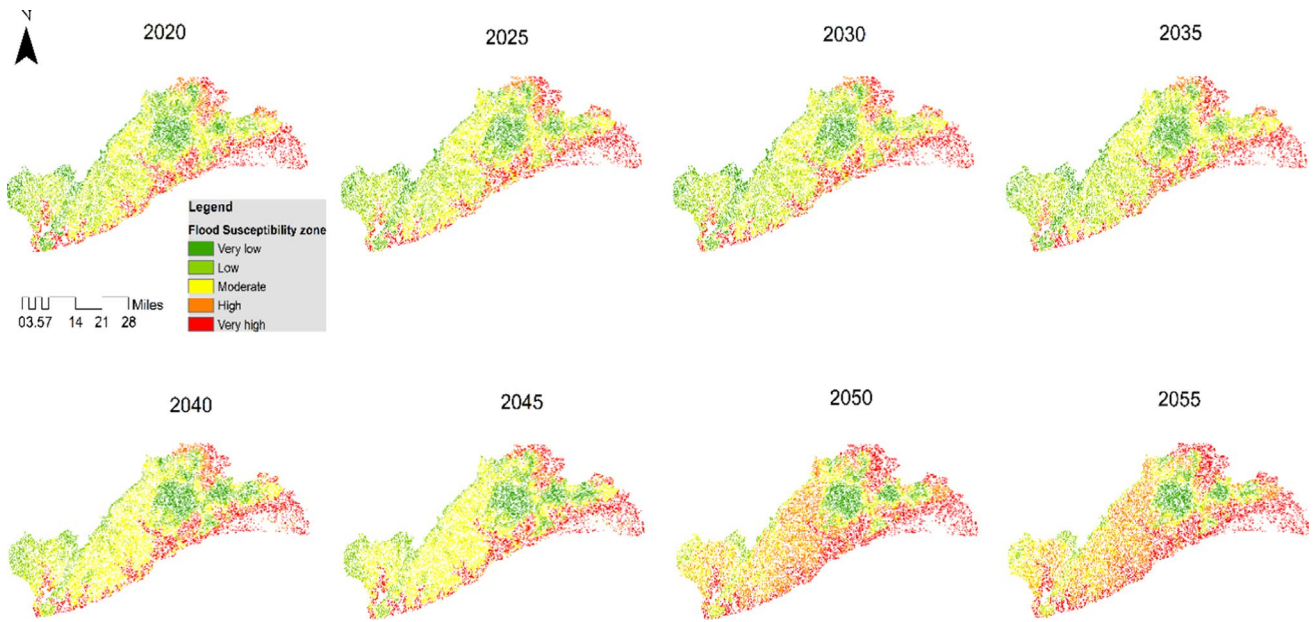


Fig. 17 Spatio-temporal distribution of flood vulnerability zones under the SSP3 scenario

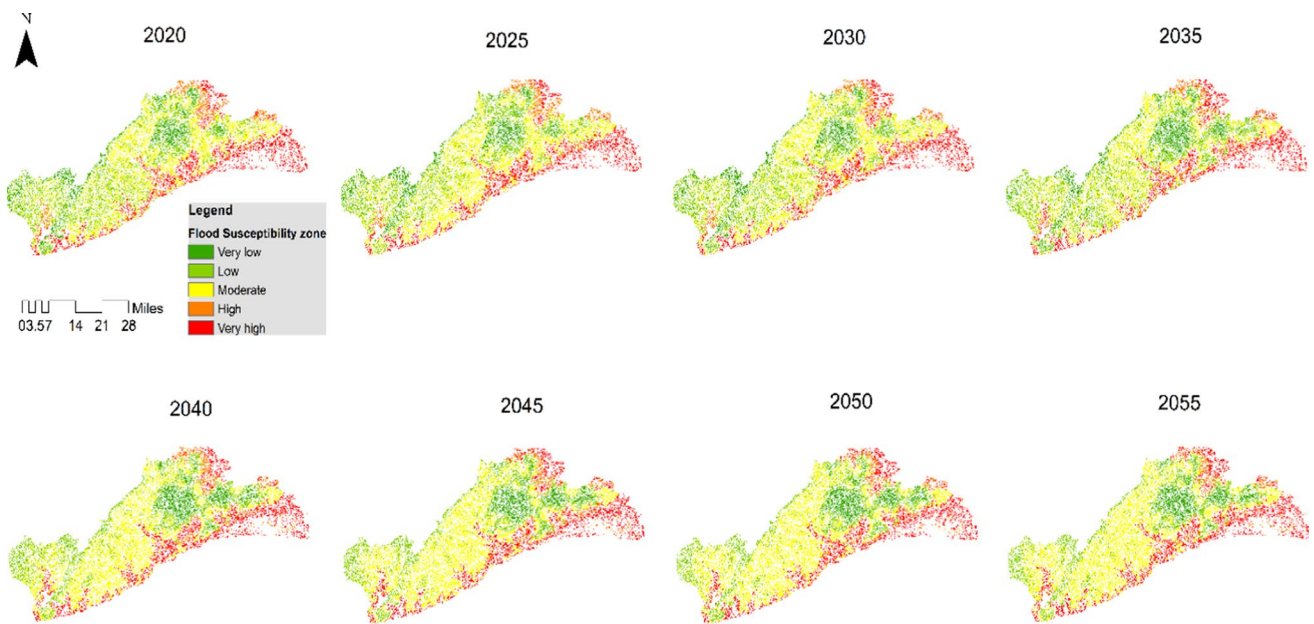


Fig. 18 Spatio-temporal distribution of flood vulnerability zones under the SSP5 scenario

Appendix 3: List of substations and their capacities

Code	Bulk supply point name	Location	Capacity (MW)
A	Shiashi ECG Substation	Legon	9.35
B	ECG Sub Station—Exhibition	Dansoman Exhibition	9.35
C	ECG Substation	Teshie Nungua	9.35
D	ECG Korle-Bu	Korle Bu	9.35
E	ECG Substation Tema	Tema Steel Works	9.35
F	Enclave Power Company substation	Tema	9.35
G	Electricity Company of Ghana Substation	Ofankor	9.35
H	GRIDCO ACCRA-EAST SUBSTATION	Accra East	28.05
I	GRIDCO—ACHIMOTA SUBSTATION	Achimota	28.05
J	E.C.G. Primary Station [Tokose Station Z]	Weija	9.35
K	ECG Substation, Airport City Substation	Airport	9.35
L	Gbawe ECG substation	Mallam	9.35
M	ECG substation 'AH' (Ministries)	Ridge	9.35
N	ECG Transformer Substation	Adenta	9.35
O	Dawhenya ECG Sub-Station	Dawhenya	9.35
P	Siemens Power Plant	Tema	9.35
Q	ECG Power Sub Station	Awoshie	9.35
R	AFIENYA BSP	Afienva	28.05
S	ECG Power Station	Legon	9.35
T	Station AE	Kwabenva	9.35
U	Makola station G	Makola	9.35
V	Station Y Bastona	Spintex, Batsona	9.35
W	Gridco accra central	adabraka	28.05
X	Graphic road	graphic road	9.35
Y	Avenor	avenor station	9.35
Z	ECG Station R	Ridge	9.35
AA	AJ	Tradefair Tseaddo	9.35
AB	Station X	Osu Kuku hill	9.35
AC	AU	Cantoments	9.35
AD	A-ECG substation	Odorkor	9.35
AE	Station L	Burma Camp	9.35
AF	ECG substation AS	Kanda substation	9.35
AG	Station K	Switchback, cantoments	9.35
AH	ECG station SW	Sowutuom	9.35
AI	Station AP	Polo grounds	9.35
AJ	Station F	Kokomlemle	9.35
AK	ECG substation AW	Awudome	9.35
AL	ECG substation S	Kwashieman	9.35
AM	ECG substation AL	Darkuman	9.35
AN	ECG substation A	Odorkor	9.35
AO	ECG substation AN	GIMPA	9.35
AP	Station Q	Tema—Meridian	9.35
AQ	Station A	TdC	9.35
AR	Station B	Comm 12	9.35
AS	Station C	Comm 25	9.35

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