GIS-Based Multi-Criteria Analytical Hierarchy Process Modelling for Urban Flood Risk Analysis and Assessment, Accra Metropolis

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Research Article

Keywords: Flood, geographical information system (GIS), remote sensing, multi-criteria decision analysis (MCDA), analytical hierarchy process (AHP).

Posted Date: July 1st, 2022

DOI: https://doi.org/10.21203/rs.3.rs-1712549/v1

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Abstract

A series of devastating flood events within the Accra Metropolis over the last decades have demonstrated the urgent need for urban resilience. The present work aimed to develop a GIS-based model to analyse and assess floods in the Accra Metropolis. The framework is based on the Multi-Criteria Analytical Hierarchy Process within the GIS platform. Relevant thematic layers including LULC, Elevation, Slope, Soil, and Drainage density were generated within the GIS environment. In the context of objective weight assignments, the AHP algorithm was successfully applied to create flood hazard indices, and then the urban flood risk maps were constructed for 2007, 2010, 2015 and 2020. The findings revealed that areas under high and very high flood risk have increased from 55.163–60.043% over the last decade and a half. A flood inventory map was produced by randomly mapping 256 flood test locations to determine the model's performance. These locations consisted of 128 flooded and 128 non-flooded points extracted from historical flood data, ground truth data and high-resolution satellite imagery. The computed Receiver Operating Characteristic (ROC) curve showed an Area Under the Curve (AUC) value of 0.916, indicating an excellent correlation between the analysed flood risk areas and the ground truth data. Findings from the study will assist decision-makers in formulating medium-long term mitigation measures to reduce flood-related damages and employ proper future land-use planning.

1. Introduction

Urban areas are some of the most sensitive systems to hydrological extremes; flood variability, fluctuations and changes, presenting alongside a wide range of impacts on society and the environment (Hapuarachchi et al., 2011; Lewin, 2013; Tarolli and Sofia, 2016). Over the years, climatic conditions coupled with numerous land-use changes have caused profound metamorphosis to natural hydrological processes (Sofia et al., 2017). These alterations underscore enormous repercussions on urban flood regimes, whose sensitivity to changes exacerbates with rapid urbanization and extreme rainfall events (Amoako et al., 2014; Jumadar et al., 2008). Urbanised landscapes, where impervious and bare areas cover extensive land surfaces are characterized by reduced infiltration and accelerated runoff which tends to increase the frequency and intensity of flood events (Chen et al., 2009; Leopold, 1968; Mojaddadi et al., 2017). Chen et al., (2009) and Albuquerque et al., (2019) further emphasized that the urban environment's waterproofed surfaces obstruct natural drainage channels or increase the likelihood that surface runoffs overwhelm the drainage capacity.

settlements in low-lying and flood-prone areas (Amoako et al., 2014; Amoako and Inkoom, 2018; Douglas et al., 2008) and poor waste management (Karley, 2009); as major drivers for flood occurrences.

Notwithstanding, several researchers in hydrology have made significant advances in providing sound underpinnings for understanding various hydrological theories and empirical models to simulate and predict the overall behaviour of urban floods (Guo et al., 2021; Merz et al., 2010; Prosdocimi et al., 2015). Haq et al., (2012) believed that these advances have provided a tremendous potential to fulfil the requirements for flood prediction, preparation, prevention, and damage analysis. The application of GIS and remote sensing technologies in flood modelling has emerged as a pivotal technology enabling better planning and action for both strategic and tactical needs required to successfully overcome the challenges of the increasingly complex task of modelling and predicting the dynamics of urban hydrology processes. Several studies including Chen et al., (2009); Wang et al., (2011); Kablan et al., (2017); Kwang and Osei (2017); Paul et al., (2019); Sayed and Haroon, (2019); and Ogato et al., (2020)) have shown results of the application of hydrological methods and flood modelling approaches using GIS and RS platforms in solving flood risk problems in urban watersheds with significantly enhanced accuracy. Given that flood hazard is a spatial phenomenon, the attractiveness of GIS and RS techniques are with their abilities to process spatial data, visualize the extent of flooding, analyse flood risk and estimate damage for prompt and effective decision-making (Ogato et al., 2020; Uddin et al., 2013).

Multi-Criteria Decision Analysis (MCDA) methods provide decision support tools for dealing with natural resource management issues and other complex decision constellations (Myagmartseren et al., 2017). These methods have been repeatedly applied with the combination of GIS in mapping and assessing flood risk (Lin et al., 2019; Prasad and Narayanan, 2016; Saha and Agrawal, 2020). The GIS-based MCDA inputs data and combines the output into weighted maps based on the ability of GIS to manage geospatial data (data acquisition, storage, retrieval, manipulation, and analysis) and the flexibility of MCDA to combine geographical data with value-based information or the decision maker’s preferences into unidimensional values of alternative decisions (Stefanidis and Stathis, 2013; Wang et al., 2011; Yahaya et al., 2010). This approach continues to demonstrate great promises at enhancing the effectiveness and efficiency of decision-making in urban flood modelling.

However, existing research studies in the Accra Metropolis have not conclusively established GIS-based MCDA-AHP approaches as optimum means to modelling urban flood vulnerability. The few existing randomized studies have only focused on one-time flood risk analysis (Kwang and Osei, 2017; Nyarko, 2000; Dekongmen et al., 2021). The present study addresses part of the issues by demonstrating the strong capabilities of GIS and remote sensing in simulating the Spatio-temporal complexity of land-use modelling. Within this framework, the study used established principles and criteria by other researchers to assess urban flood vulnerability from a series of flood years. The GIS-based multi-criteria AHP model provided practical decision support for determining the contributing factors for flood inundation in vulnerable communities within the Accra Metropolis. Most significantly, the findings from the present study will influence the decision-making process and serve as a benchmark to improve flood planning in urban areas in developing countries.
2. Materials And Methods

2.1 Study Area Description

The study was based in Accra Metropolis, which is the administrative and commercial capital of Ghana. Located in the south eastern, and bordered with the Gulf of Guinea, the city sits partly on a cliff of about 8 to 12 meters high and spreads north over the Accra plains. The area lies between latitude 5°35'01"N and longitude 0°1'13"W and covers a total land surface area of approximately 140km$^2$ (Fig. 1). Almost flat and featureless, the plains of Accra descend gradually to the Gulf of Guinea from a height of about 150 metres. Characterized by low relief topography with occasional hills, the slope of the city is gentle at below 11%, with a water table varying between 4.80 and 70 m below the surface (Nyarko, 2000). The precipitation patterns in Accra have changed considerably within the last few decades, with an upsurge in the average monthly precipitation from 160 mm in 1991–2010 to 200 mm in 2011–2020, where May and June continue to experience the maximum average downpours. It is during these periods that the city experiences catastrophic flood inundations (Asumadu-Sarkodie et al., 2015).

Generally, the area has witnessed a statistically significant trend towards urban sprawl and uncontrolled expansion from its urban boundaries into marginal lands over the past 50 years. The recorded urban population between 1970–1984 and 2000–2010 depicted an increase from 624,091 to 969,195 and 1,658,937 to 2,070,463 respectively (Ghana Statistical Service, 2013). Currently, the estimated population stands at 2,556,972 (World Population Review, 2020). According to Amoako et al., (2014) and Okyere et al., (2013), the exposure and vulnerability of Accra to flood hazards have resulted from rapid urbanization coupled with the uncontrolled growth of informal settlements in low-lying and flood-prone areas.

2.2 Conceptual Framework

The adapted conceptual framework briefly illustrates the path of the study and grounds it firmly in theoretical constructs. The concept has been woven together in a paradigm of relationships simplified in the flowchart (Fig. 2).

2.3 Data Acquisition and Collection

The spatial database used in the GIS-based Multi-Criteria Analytical Hierarchy Process (AHP) model for analysing and predicting the urban flood risk in the Accra Metropolis, was developed using a variety of data gathered from remote sensing sources on various dates at different scales (Table 1). Satellite imageries were obtained from Landsat archives of the United States Geological Survey (USGS) official database and Copernicus Open Access Hub. Free available Advanced Space-borne Thermal Emission and Reflection Radiometer (ASTER); Global Digital Elevation Model (GDEM) was downloaded from the ASTER Platform. Digital Soil Map of the World was downloaded from the Food and Agriculture Organization (FAO) of the United Nations database. Finally, the resultant flood inventory map of the study area was produced from 256 GPS (Global Positioning System) coordinates of both flooded and non-flooded areas. These statistical locations gathered during the study period were acquired from documentary sources of the National Disaster Management Organisation (NADMO) and field survey.
Table 1: Data sources and types presented in the study

<table>
<thead>
<tr>
<th>Data</th>
<th>Sources (URL)</th>
<th>Type</th>
<th>Date/Period</th>
</tr>
</thead>
<tbody>
<tr>
<td>Satellite Image</td>
<td>USGS <a href="http://earthexplorer.usgs.gov">http://earthexplorer.usgs.gov</a></td>
<td>Landsat 7 ETM+; 30m spatial resolution; 8 spectral bands; cloud coverage 0–10%</td>
<td>2007/01/06 (path/row-193/056)</td>
</tr>
<tr>
<td></td>
<td>Copernicus Open Access Hub <a href="https://scihub.copernicus.eu">https://scihub.copernicus.eu</a></td>
<td>Landsat 8 OLI; 30m spatial resolution; cloud coverage 0–10%</td>
<td>2010/03/03 (path/row-193/056)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Sentinel 2A; 10m, 20m, 60m spatial resolution; 13 spectral bands; cloud coverage 0–10%</td>
<td>2015/01/04 (path/row-193/056)</td>
</tr>
<tr>
<td>Digital Elevation Model (DEM)</td>
<td>ASTER Platform <a href="https://asterweb.jpl.nasa.gov/gdem.asp">https://asterweb.jpl.nasa.gov/gdem.asp</a></td>
<td>ASTER GDEM version 3; 30m spatial resolution;</td>
<td>2019/08/05</td>
</tr>
<tr>
<td>Flood Inventory Data</td>
<td>National Disaster Management Organization (NADMO) - Accra; Field survey</td>
<td>GPS coordinates of 256 historical flood and non-flood locations</td>
<td>2007; 2010; 2015; 2020</td>
</tr>
</tbody>
</table>

2.4 Flood Parameter Selection

The identification and selection of appropriate criteria is vital to accurately described flood-prone areas (Kazakis et al., 2015; Lin et al., 2019). Previous studies including Danumah et al., (2016); Elkhrachy, (2015); Fernndez and Lutz (2010); Stefanidis and Stathis (2013); and Youssef et al., (2016) used various criteria in correspondence to local geographical settings that influence the physical process of flood mechanism. Yalcin (2008) acknowledged that, in GIS-based studies, the selection of causal factors takes into account the nature of the study area and the data availability. But further emphasized the necessity to select factors based on; the operation (a certain degree of affinity with the phenomenon), coverage (fairly represented all over the study area), non-uniformity (varies spatially), measurability (expressed by nominal, ordinal, interval, ratio scales), and non-redundancy (effect should not account for double consequences in the final result). Synthesis of these criteria led to the derivation of five urban flood contributing and intensifying factors, taking into account data availability, key informant interviews and their relevance to flood hazards as documented in the literature. Input data for each parameter was processed and visualized within the GIS environment as thematic data layer input for setting up the model for the flood simulation and predicting. The thematic layers representing (1) LULC, (2) Elevation, (3) Slope, (4) Soil, and (5) Drainage density were identified as important factors that accurately describe
flood susceptibility in the study area. Apparently, the selected parameters have proven effective having been included in relevant research studies and applications (Kia et al., 2012; Kwang and Osei, 2017).

**2.5 Data Processing and Analysis**

**2.5.1 Satellite Image Processing and LULC classification**

Mojaddadi et al., (2017) addressed the crucial role LULC plays in flood hazard modelling, when it is considered as a conditioning factor and criteria for vulnerability assessment. According to Shuster et al., (2005), an increase in the proportional area under impervious surfaces is primarily responsible for the hydrologic changes associated with the urbanization process. The alteration of landscapes through this process accounts for shrinkages in vegetation cover (Jha et al., 2012), fragmentation and drainage of wetlands (Hopkinson and Day, 1980), reduced infiltration rate and decreased drainage capacity (Jumadar et al., 2008; McGrane, 2016). Intuitively, these changes present alongside shorter lag times between the onset of precipitation and subsequently higher runoff peaks and high volume of runoff in receiving waters. Bhatt et al., (2014) however acknowledged that the application of accurate LULC map can improve the results of flood risk analysis. Thus, to acquire spatially comprehensive information in the present study, satellite images dating from 2007, 2010, 2015 and 2020 were processed in two phases: pre-processing and image processing. Within the image processing phase, the supervised maximum likelihood classification method was applied to categorize the scenes into various LULC classes. Based on prior knowledge of the study area, five main land-use types were identified; dense vegetation, open vegetation, bare area, built-up area and wetland (Table 2). Images from different sensors tend to have different spatial resolutions. Thus, satellite images of 30m spatial resolution were resampled to a higher spatial resolution of 10m.

<table>
<thead>
<tr>
<th>LULC type</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dense Vegetation</td>
<td>Forest reserve or densely populated trees.</td>
</tr>
<tr>
<td>Open Vegetation</td>
<td>Widely dispersed trees, scrublands, grasslands, recreational parks, domestic lawns or road verges</td>
</tr>
<tr>
<td>Bare Area</td>
<td>Barren lands, beaches, rocks, wasteland and other empty lands</td>
</tr>
<tr>
<td>Built-up Areas</td>
<td>Construction lands or impervious surfaces; including, commercial and industrial sites, warehouses, factories, paved surfaces (roads, parking lots), residential areas, public administrations, or public services</td>
</tr>
<tr>
<td>Bare Area</td>
<td>Barren lands, Rocks, Fallow land, Wasteland, Construction sites, Excavation sites, Open space, Bare soils, and other empty lands.</td>
</tr>
<tr>
<td>Wetland</td>
<td>Waterbodies, reservoirs, streams, marshes, swamps, saturated lands, fish ponds, or drainages</td>
</tr>
</tbody>
</table>

**2.5.2 Digital Elevation Model (DEM) Processing**
The topographic data represented by ASTER GDEM, with a spatial resolution of 30 was used to analyse the geomorphometric parameters, including elevation, slope, and drainage density. The thematic maps of these parameters were prepared and reclassified accordingly, where weight values were assigned to various classes based on a systematic flood hazard index using the ArcGIS spatial analyst tool.

### 2.5.3 Elevation Mapping

Regions at lower elevations have higher flood vulnerability than high elevated regions as water flows downhill (Das, 2018). Sayed and Haroon (2019) further emphasized that low-lying zones are first inundated followed by the higher elevations in the proximity. Flood studies including Kia et al., (2012) and Aryal et al., (2020) also acknowledged the significance of including elevation analysis to accurately simulate flood inundation. The elevation map of the study was however prepared by reclassifying the DEM range of values into five classed groups using the Jenks natural break classification scheme (Jenks, 1967).

### 2.5.4 Slope Mapping

Slope gradient significantly influences surface runoff and flooding (Jourgholami et al., 2021; Saini et al., 2016). According to Rahmati et al., (2016) and Saha and Agrawal (2020), the steepness of slopes is a major factor in determining the amount of surface runoff, runoff velocity and percolation rate. Low gradient slopes at lower reaches may offer quicker flood inundation and water-logging compared to high gradient slopes (Gigović et al., 2017; Rimba et al., 2017). The slope gradient was computed using the DEM, based on the slope model where the rate of change (delta) of the surface in the horizontal ($\text{Slope}_{\text{we}}$) and vertical ($\text{Slope}_{\text{sn}}$) directions from the centre cell determines the slope gradient. This is calculated in the algorithm as expressed in Eqs. (1) and (2) (Burrough, 1986).

$$\text{Slope}_{\text{degrees}} = \frac{\text{ATAN} \left( \text{rise}_{\text{run}} \right) \times 180}{\pi}$$ (1)

$$\text{rise}_{\text{run}} = \sqrt{\text{Slope}_{\text{we}}^2 + \text{Slope}_{\text{sn}}^2}$$ (2)

The values of the centre cell and its eight neighbours determine the horizontal and vertical deltas. The neighbours are identified as letters from “$e_1$” to “$e_8$”, with “e” representing the cell for which the aspect is calculated. The rate of change in the horizontal and vertical directions for cell “e” is calculated based on Eqs. (3) and (4).

$$\text{Slope}_{\text{we}} = \frac{(e_8 + 2e_4 + e_5) - (e_7 + 2e_3 + e_6)}{8 \times \text{cellsize}}$$ (3)

$$\text{Slope}_{\text{sn}} = \frac{(e_7 + 2e_4 + e_8) - (e_6 + 2e_2 + e_5)}{8 \times \text{cellsize}}$$ (4)
The resultant slope map of the study area was calculated in degree and reclassified into five classes under the Jenks natural break clustering technique between limits of 0 and 32°.

### 2.5.5 Drainage Density Mapping

Drainage density describes the ratio of the total length of all streams within the drainage basin to the total area of the basin (Horton, 1945; Ogden et al., 2011; Pallard et al., 2009). In deriving the drainage density of the streams for the catchment area, the drainage network was estimated by computing the flow direction grid and flow accumulation grid. Drainage density was calculated using the formula in Eq. (5) (Bredensteiner and Strittholt, 2002).

\[
\text{Drainage density } (D_d) = \frac{\text{total length channels (km)}}{\text{basin area (km}^2\text{)}}
\]  

(5)

The drainage density of the study area was divided into five classes using the Jenks natural break classification scheme.

### 2.5.6 Soil Mapping

Kwang and Osei (2017) stated that soil permeability is one of the parameters used to determine the soil infiltration capacity. Thus, soils with higher clay content reduce water infiltration capacity due to the higher resistance to free flow through these soil types, thereby increasing the amount of surface runoff that can lead to flooding. The soil map of the study area was prepared through the rasterization of the vector map published by the FAO. The map was divided into four major soil groups; Acrisols, Luvisols, Plinthosols and Waterbody/Wetland.

### 2.5.7 Integration of AHP into Geographic Information Systems

The AHP method established by Saaty (1980) was adopted for the multi-criteria decisions. This semi-quantitative approach allows criteria weight estimation based on expert viewpoints of the relative importance of each criterion to flood risk (Nascimento et al., 2017; Pourghasemi et al., 2016). The present study, however, relied on the experts’ judgement of the hydrological conditions and disaster management supported by relevant literature to prepare a pairwise comparisons matrix. The multiple pairwise comparisons are based on a standardized scale of nine levels that can be compared simultaneously and ranked consistently (Saaty, 1977) (Table 3). The pairwise judgements are made based on the best information available and the decision maker's knowledge and expertise (Saaty, 2008).
Table 3
Nine-point pairwise comparison scale (Saaty, 1980)

<table>
<thead>
<tr>
<th>Intensity of importance</th>
<th>Definition</th>
<th>Explanation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Equal importance</td>
<td>Two elements contribute equally to the objective.</td>
</tr>
<tr>
<td>3</td>
<td>Moderate importance</td>
<td>Experience and judgment slightly favour one parameter over another.</td>
</tr>
<tr>
<td>5</td>
<td>Strong importance</td>
<td>Experience and judgment strongly favour one parameter over another.</td>
</tr>
<tr>
<td>7</td>
<td>Very strong importance</td>
<td>One parameter is favoured very strongly and is considered superior to another; its dominance is demonstrated in practice.</td>
</tr>
<tr>
<td>9</td>
<td>Extreme importance</td>
<td>The evidence favouring one parameter as superior to another is of the highest possible order of affirmation.</td>
</tr>
</tbody>
</table>

Note: 2, 4, 6, 8 can be used to express intermediate values for parameters that are very close in importance.

Khan and Samadder (2015) summarized a sequential step for AHP determination. The process comprised; (i) computing the sum of values in each column of a pairwise comparison matrix, (ii) normalizing the matrix by dividing each element by its column total, and (iii) computing the mean of the elements in each row of the normalized matrix.

2.5.8 Criteria Weight Assignment using AHP

As an initial part of the AHP process, a pairwise comparison matrix was performed for all the five criteria. In the pairwise comparison matrix, the rows follow the inverse value of each factor and its significance with the other. Thus, for the five criteria, 10 non-trivial pairwise comparisons were defined (Table 5). The result of the pairwise comparison on the number of criteria is summarized in an evaluation matrix, $A$, where every element $a_{ij}$ ($i, j = 1, 2, ..., n$) is the quotient of weights of the criteria, as depicted in Eq. (6).

Table 4
Random index (RI) used to compute consistency ratios (CR)

<table>
<thead>
<tr>
<th>N</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0</td>
<td>0</td>
<td>0.58</td>
<td>0.90</td>
<td>1.12</td>
<td>1.24</td>
<td>1.32</td>
<td>1.41</td>
<td>1.45</td>
<td>1.49</td>
</tr>
</tbody>
</table>
Table 5
Pairwise combination matrix of criteria significance

<table>
<thead>
<tr>
<th>Parameters</th>
<th>LULC</th>
<th>Elevation</th>
<th>Slope</th>
<th>Soil Type</th>
<th>Drainage Density</th>
</tr>
</thead>
<tbody>
<tr>
<td>LULC</td>
<td>1.00</td>
<td>2.00</td>
<td>3.00</td>
<td>5.00</td>
<td>6.00</td>
</tr>
<tr>
<td>Elevation</td>
<td>0.50</td>
<td>1.00</td>
<td>2.00</td>
<td>3.00</td>
<td>4.00</td>
</tr>
<tr>
<td>Slope</td>
<td>0.33</td>
<td>0.50</td>
<td>1.00</td>
<td>2.00</td>
<td>3.00</td>
</tr>
<tr>
<td>Soil Type</td>
<td>0.20</td>
<td>0.33</td>
<td>0.50</td>
<td>1.00</td>
<td>2.00</td>
</tr>
<tr>
<td>Drainage Density</td>
<td>0.17</td>
<td>0.25</td>
<td>0.33</td>
<td>0.50</td>
<td>1.00</td>
</tr>
</tbody>
</table>

Note. $\lambda_{\text{max}}$ represents the sum of the products between each column of the comparison matrix and the relative weights. The resulting weights are based on the principal eigenvector of the decision matrix.

The values in the pairwise comparison are normalized to acquire the normalized values in the standard pairwise comparison matrix (Table 6). The relative weight for each matrix, $A_w$, is obtained based on Eq. (7).

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix}, a_{ii} = 1, a_{jj} = \frac{1}{a_{jj}}, a_{jj} \neq 0$$

$$A_w = \lambda_{\text{max}}w$$

Table 6: Normalized pairwise matrix, weights and ranking for parameters

<table>
<thead>
<tr>
<th>Parameters</th>
<th>LULC</th>
<th>Elevation</th>
<th>Slope</th>
<th>Soil Type</th>
<th>Dra. Den.</th>
<th>Normalized Priority vector $w$</th>
<th>Relative weight (%)</th>
<th>Weightage ranking</th>
</tr>
</thead>
<tbody>
<tr>
<td>LULC</td>
<td>0.45</td>
<td>0.49</td>
<td>0.44</td>
<td>0.43</td>
<td>0.38</td>
<td>0.438</td>
<td>43.8%</td>
<td>5</td>
</tr>
<tr>
<td>Elevation</td>
<td>0.23</td>
<td>0.25</td>
<td>0.29</td>
<td>0.26</td>
<td>0.25</td>
<td>0.256</td>
<td>25.6%</td>
<td>4</td>
</tr>
<tr>
<td>Slope</td>
<td>0.15</td>
<td>0.12</td>
<td>0.15</td>
<td>0.17</td>
<td>0.18</td>
<td>0.154</td>
<td>15.4%</td>
<td>3</td>
</tr>
<tr>
<td>Soil Type</td>
<td>0.09</td>
<td>0.08</td>
<td>0.07</td>
<td>0.10</td>
<td>0.13</td>
<td>0.094</td>
<td>9.4%</td>
<td>2</td>
</tr>
<tr>
<td>Dra. Den.</td>
<td>0.08</td>
<td>0.06</td>
<td>0.05</td>
<td>0.04</td>
<td>0.06</td>
<td>0.058</td>
<td>5.8%</td>
<td>1</td>
</tr>
</tbody>
</table>
2.5.9 Conformity Check

According to Lin et al., (2019), the conformity check ensures that the evaluation of the distribution of weights is assigned more scientifically. Ouma and Tateishi (2014) moreover claimed that the efficiency of an AHP output is strictly related to the consistency of the pairwise comparison judgments (Saaty, 1980). The consistency ratio (CR) however, provides an indicator of the degree of consistency or inconsistency. The AHP theory suggests that, if the consistency ratio is less than 0.1, the matrix can be considered an acceptable consistency. However, if the CR is greater than 0.10, the weight assignment is re-evaluated to avoid inconsistency. Thus, the required level of consistency for the study was evaluated using Eq. (8).

\[
CR = \frac{CI}{RI}
\]

where, CI is the consistency index and RI is the random consistency index. The CI is calculated through Eq. (9).

\[
CI = \frac{\left(\lambda_{max} - n\right)}{n-1}
\]

where, \(\lambda_{max}\) represents the principal eigenvalue of the matrix, and \(n\) is the number of criteria in the matrix. The random consistency index is derived as an average random consistency index computed by Saaty (1980). The values of RI are tabulated in (Table 4). In considering the five parameters identified for the present study, the RI value was determined as 1.12. Eventually, the consistency ratio (CR) was calculated as 0.01, an affirmation that the given pairwise weights have an acceptable consistency.

2.5.10 Mapping the Flood Risk

Following the calculation of the weights, the acquired values were processed to calculate the relative significance of each criterion and the corresponding weighting factor (w). Thus, the normalized priority vector (or the normalized principal eigenvector) was computed as the coefficient for the respective flood parameter to generate the Flood Hazard Index (FHI) as depicted in Equ. (10).

\[
FHI = \sum_{i=1}^{5} r_{ij} \cdot w_i
\]

where, \(r_{ij}\) is the rating of the \(i^{th}\) parameter for the \(j^{th}\) category; and \(w_i\) the weight of each parameter.

3 Results And Discussion
3.1 Flood Contributing Parameter Analysis

3.1.1 LULC Variation

Figure 3 presented four LULC maps of the Accra Metropolis generated for 2007, 2010, 2015, and 2020. The outcome of the estimated LULC changes from the four maps reveals diverse phases of trends and the extent of land degradation in the various LULC classes.

There is strong evidence of landscape patterns changing throughout the last one and a half-decade within the Metropolis. The results of the variation in the distributions of LULC classes recognized between 2007 and 2020 indicates that the built-up area expanded quickly by 18.98% (Table 7). This unrestrained and most often unsupervised explosion of residential, commercial and industrial development is exacerbated by the horizontal expansion of extra space needed to accommodate the rapid urbanization. The unprecedented population growth mainly attributed to migration and the rate of industrialization in the area (Akom et al., 2020). Consequently, the outcomes of this development have increased the physical urban infrastructure; informal settlements; and unplanned satellite towns on the city's outskirts, with detrimental losses to existing vegetation cover.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Dense Vegetation</td>
<td>14.19</td>
<td>12.82</td>
<td>9.81</td>
<td>9.37</td>
<td>-1.37</td>
<td>-3.01</td>
<td>-0.44</td>
<td>-4.82</td>
<td>-51.44</td>
<td></td>
</tr>
<tr>
<td>Open Vegetation</td>
<td>26.56</td>
<td>22.07</td>
<td>23.31</td>
<td>21.53</td>
<td>-4.49</td>
<td>1.24</td>
<td>-1.78</td>
<td>-5.03</td>
<td>-18.93</td>
<td></td>
</tr>
<tr>
<td>Bare Area</td>
<td>12.89</td>
<td>12.75</td>
<td>8.85</td>
<td>5.9</td>
<td>-0.14</td>
<td>-3.90</td>
<td>-2.95</td>
<td>-6.99</td>
<td>-54.22</td>
<td></td>
</tr>
<tr>
<td>Built-up Area</td>
<td>85.58</td>
<td>91.95</td>
<td>96.61</td>
<td>101.82</td>
<td>6.37</td>
<td>4.66</td>
<td>5.21</td>
<td>16.24</td>
<td>18.98</td>
<td></td>
</tr>
<tr>
<td>Wetland</td>
<td>0.68</td>
<td>0.33</td>
<td>1.29</td>
<td>1.29</td>
<td>-0.35</td>
<td>0.96</td>
<td>0.00</td>
<td>0.61</td>
<td>89.70</td>
<td></td>
</tr>
</tbody>
</table>

Note: Δ represents the difference in area changes

The accuracy of each classified image was evaluated through the confusion matrix. The resultant overall accuracy, kappa statistics, user accuracy and the producer accuracy of individual classes for each year of the LULC (Table 8).
Table 8
Accuracy assessment of LULC classification

<table>
<thead>
<tr>
<th>LULC Class</th>
<th>2007</th>
<th>2010</th>
<th>2015</th>
<th>2020</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>PA(%)</td>
<td>UA(%)</td>
<td>PA(%)</td>
<td>UA(%)</td>
</tr>
<tr>
<td>Dense Vegetation</td>
<td>90.32</td>
<td>88.76</td>
<td>83.65</td>
<td>86.49</td>
</tr>
<tr>
<td>Open Vegetation</td>
<td>86.11</td>
<td>88.24</td>
<td>87.41</td>
<td>85.54</td>
</tr>
<tr>
<td>Bare Area</td>
<td>88.53</td>
<td>91.30</td>
<td>72.23</td>
<td>68.96</td>
</tr>
<tr>
<td>Built-up Area</td>
<td>91.56</td>
<td>92.69</td>
<td>84.11</td>
<td>86.07</td>
</tr>
<tr>
<td>Wetlands</td>
<td>87.81</td>
<td>87.14</td>
<td>39.09</td>
<td>41.65</td>
</tr>
<tr>
<td>Overall Accuracy</td>
<td>89.42%</td>
<td>69.25%</td>
<td>83.78%</td>
<td>87.81%</td>
</tr>
<tr>
<td>Kappa Statistics</td>
<td>0.881</td>
<td>0.683</td>
<td>0.841</td>
<td>0.873</td>
</tr>
</tbody>
</table>
### Table 9
Statistics of flood contributing parameter and associated ratings

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Class</th>
<th>Area (km²)</th>
<th>Percent (%)</th>
<th>Weight</th>
<th>FHI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Elevation (meters)</td>
<td>82–170</td>
<td>8.10</td>
<td>5.8</td>
<td>1</td>
<td>Very Low</td>
</tr>
<tr>
<td></td>
<td>59–82</td>
<td>16.34</td>
<td>11.7</td>
<td>2</td>
<td>Low</td>
</tr>
<tr>
<td></td>
<td>39–59</td>
<td>25.21</td>
<td>18.1</td>
<td>3</td>
<td>Moderate</td>
</tr>
<tr>
<td></td>
<td>21–39</td>
<td>40.50</td>
<td>29.0</td>
<td>4</td>
<td>High</td>
</tr>
<tr>
<td></td>
<td>0–21</td>
<td>49.50</td>
<td>35.4</td>
<td>5</td>
<td>Very High</td>
</tr>
<tr>
<td>Slope (degree)</td>
<td>12.81–32.04</td>
<td>3.21</td>
<td>2.3</td>
<td>1</td>
<td>Very Low</td>
</tr>
<tr>
<td></td>
<td>8.29–12.82</td>
<td>13.16</td>
<td>9.6</td>
<td>2</td>
<td>Low</td>
</tr>
<tr>
<td></td>
<td>5.28–8.29</td>
<td>27.80</td>
<td>20.1</td>
<td>3</td>
<td>Moderate</td>
</tr>
<tr>
<td></td>
<td>2.76–5.28</td>
<td>47.89</td>
<td>34.8</td>
<td>4</td>
<td>High</td>
</tr>
<tr>
<td></td>
<td>0.00–2.76</td>
<td>45.69</td>
<td>33.2</td>
<td>5</td>
<td>Very High</td>
</tr>
<tr>
<td>Soil Type</td>
<td>Acrisols</td>
<td>128.37</td>
<td>91.9</td>
<td>2</td>
<td>Low</td>
</tr>
<tr>
<td></td>
<td>Luvisols</td>
<td>1.40</td>
<td>1.0</td>
<td>3</td>
<td>Moderate</td>
</tr>
<tr>
<td></td>
<td>Plinthosols</td>
<td>9.04</td>
<td>6.5</td>
<td>4</td>
<td>High</td>
</tr>
<tr>
<td></td>
<td>Waterbody/Wetlands</td>
<td>0.78</td>
<td>0.6</td>
<td>5</td>
<td>Very High</td>
</tr>
<tr>
<td>Drainage Density (Km Km⁻²)</td>
<td>4.81–6.01</td>
<td>0.48</td>
<td>0.3</td>
<td>1</td>
<td>Very Low</td>
</tr>
<tr>
<td></td>
<td>3.61–4.81</td>
<td>4.57</td>
<td>3.3</td>
<td>2</td>
<td>Low</td>
</tr>
<tr>
<td></td>
<td>2.41–3.61</td>
<td>39.04</td>
<td>28.0</td>
<td>3</td>
<td>Moderate</td>
</tr>
<tr>
<td></td>
<td>1.20–2.41</td>
<td>83.07</td>
<td>59.5</td>
<td>4</td>
<td>High</td>
</tr>
<tr>
<td></td>
<td>0.00–1.20</td>
<td>12.50</td>
<td>8.9</td>
<td>5</td>
<td>Very High</td>
</tr>
</tbody>
</table>

### 3.1.2 Elevation Analysis

The result indicated that 35.4% of the study area, predominately within the southern central portions fall within very low elevations between 0 and 21 m (Fig. 4a). These areas are considered to have a high vulnerability to flooding due to logging of water drained from surrounding uplands and their sub-catchment. Higher weights were assigned to these lower elevations, and lower weights to higher elevated surfaces.

### 3.1.3 Slope Analysis
Figure 4 (b) depicts the slope gradient for the study area. Generally, regions that fall within high gradients of the Metropolis reduce infiltration processes, presenting increases in surface runoff. A greater percentage of the Metropolis is covered with slope gradient between 0° to 5°, which favours the southern and central part of the catchment to receive high volumes of runoff. These volumes of water can inundate low elevated areas and surrounding catchments to possibly result in flooding.

### 3.1.4 Soil Analysis

Acrisols occupy the most dominant of the study area. Plinthosols are found mainly along the western part of the area, whereas small patches of Luvisols are located in the north-eastern part of the study area. Both Luvisols and Acrisols are characterized by clay accumulation but with different base statuses. These soils are poorly drained and subject to seasonal flooding. This condition adversely affects the water retention capacity of the soils. Plinthosols have fragments of indurated plinthite and sheet iron-pan, which also hinder the internal drainage of the soils. The highest weight was assigned to wetland, as these areas have the lowest permeability rate and very high risk to flooding hazard. Plinthosols, Luvisols and Acrisols were ranked as high, moderate, and low risk respectively. The spatial distribution of the major soil series is illustrated in Fig. 4 (c).

### 3.1.5 Drainage Density Analysis

The spatial variation in drainage density as depicted in Fig. 4 (d) indicates that higher portions of the Metropolis fall within areas with low to very low drainage density areas. However, Ibrahim-Bathis and Ahmed (2016), posited that, drainage density is an inverse function of permeability and significant in the runoff distribution and the rate of infiltration. The higher the drainage density, the lower the infiltration rate and the higher the surface flow velocity (Yalcin, 2008). Dense and denser drainage densities were observed within the middle through to the south-central part of the study.

### 3.1.6 Flood Risk Mapping in Accra Metropolis

The resultant flood risk maps of the various flood years exhibit hazard indices ranging from very low to very high-risk probability (Table 10). As depicted in Fig. 5 (a) the area ratio of the different risk levels in 2007 covered 1.354%, 15.105%, and 28.379% representing very low risk, low risk, and moderate risk areas respectively. Areas with high and very high risks covered 54.613% and 0.55% respectively. In 2010 Fig. 5 (b), high-risk areas quickly increased by 6.77%. Meanwhile, low and moderate-risk areas showed a noticeable 7.61% and 8.29% declination, respectively, within this period. The next phase, 2015 (Fig. 5 (c)), depicted a slight to marginal increase in high-risk areas by 1.15%. Moreover, very risk areas expanded massively by 73.33% between 2010 and 2015. On the contrary, areas covering very low and low-risk showed 20.52% and 5.13% shrinkage, respectively, in area extent. Flood risk in 2020 (Fig. 5 (d)) depicted an increase of 0.85% in high-risk areas with a significant loss of 25.17% in very low-risk area. Also, low and moderate risk areas accounted for slight losses of 0.44% and 0.61% respectively. However, High-risk areas did not show any significant change flood risk in between 2015 and 2020 (Fig. 5 (c) and (d)).
### Table 10
Flood risk statistics in Area (square kilometres) and Percentage

<table>
<thead>
<tr>
<th>FHI</th>
<th>2007 Area (km²)</th>
<th>2010 Area (km²)</th>
<th>2015 Area (km²)</th>
<th>2020 Area (km²)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>%</td>
<td>%</td>
<td>%</td>
<td>%</td>
</tr>
<tr>
<td>Very Low Risk</td>
<td>1.87</td>
<td>1.9</td>
<td>1.51</td>
<td>1.13</td>
</tr>
<tr>
<td>Low Risk</td>
<td>20.88</td>
<td>19.29</td>
<td>18.3</td>
<td>18.22</td>
</tr>
<tr>
<td>Moderate Risk</td>
<td>39.22</td>
<td>35.97</td>
<td>36.1</td>
<td>35.88</td>
</tr>
<tr>
<td>High Risk</td>
<td>75.48</td>
<td>80.59</td>
<td>81.52</td>
<td>82.21</td>
</tr>
<tr>
<td>Very High Risk</td>
<td>0.76</td>
<td>0.45</td>
<td>0.78</td>
<td>0.78</td>
</tr>
</tbody>
</table>

Strong empirical evidence suggests variations in flood risk distribution between 2007 and 2020 within the Accra Metropolis. The map analysis showed that areas mainly sited along the south-central and the south-western portions of the Metropolis depicted very high flood potential with a slight increase from 0.55–0.566% within the last one and a half-decade. Wetlands within Mpose and catchments of the Odaw River and Korle Lagoon were identified to suffer serious flood problems due to the overflow of its banks surrounding low-lying areas. Notably, the Odaw River slopes downstream from the north through other sections to the Korle Lagoon and finally enters the Gulf of Guinea in the south. Findings in the present study are in agreement with previous studies which suggests that settlements close to banks and tributaries of the Odaw river, from Dzorwulu through Alajo, Abelemkpe, Tesano, Avenor and Adabraka to the Korle Lagoon, are at very high risk of flood occurrences during the rainy season (Karley, 2009). According to the Greater Accra Resilient and Integrated Development Project (2019), the Odaw and Korle channels are narrowed by solid waste pollution from densely populated surrounding settlements. In addition, altitudes impede water flow during storms and force the drains to overflow their banks into adjacent lowlands, causing flooding.

Encroachments, especially by slum populations, will exacerbate present flood vulnerabilities to informal settlements near the Odaw river. Furthermore, the most compelling evidence reveals that areas with a high-risk flooding potential increased steadily by 8% in extent between 2007–2020. These areas are situated on the south-central portion of the Metropolis, where the combination of low-lying topography and the extensive built-up environment favours the accumulation of runoff. Areas identified at high risk of flooding during the rainy season were communities within Awoshie, Adabraka, Ablekuma, Abelemkpe, Alajo, Tesano, Lartebiokorshie, Kwame Nkrumah Circle, Osu, Tudu, Mpose, Nima, Mataheko and portions of East Legon. This finding is further supported by the Accra Metropolitan Assembly (AMA) report in 2018, which identified these areas as flood-prone zones (Nyabor, 2018).
The situation is further exacerbated by intensive rainfall (Amoako et al., 2014) and horizontal expansion of the communities around the Central Business District into the peri-urban towns due to rapid urbanization, mainly attributed to migration and industrialization in the area where urban sprawl is at its peak. In addition, sites that showed 28.379% moderate risk of flood potentiality in 2007 declined by 33.42% in 2020. These locations predominate in low to high elevated areas with open vegetation concentrated in the eastern part. In effect, small patches of these moderate flood risk areas are scattered across the Metropolis. The northern section of the Metropolis, where the topography shows a sudden change of magnitude, indicates low to the very low potentiality of flooding between 2007 and 2020 as elevation is very high in these zones with slope angles greater than 12°. These regions do not favour the accumulation of water and the process of stagnation. However, the presence of extensive vegetation cover reduces the amount of excess surface runoff leading to flood disasters. The very low and low flood probability areas showed shrinkage within the years 2007 and 2020 by 39.59% and 12.74% respectively. Based on ground truth, residential settlements within the University of Ghana, Christian Village, and portions of East Legon and surrounding communities which initially were characterized by few populations and low urbanization, have seen consistent encroachment over the years. From critical analysis, these areas could be at risk of flooding in the future due to uncontrolled urbanization.

3.1.7 Identification and Model validation

The accuracy and quality of a developed model can be validated by comparing the acquired flood probability map with existing flood data (Talukdar et al., 2020). In the present study, quantitative validation was carried out with 256 ground truth points, 128 of the points were found to be within the perennial flood zones and 128 non-flooded points. Basically, these points overlaid on the predicted AHP flood risk map, to determine the correlation between past flood events and their drivers for estimating future flood occurrences. The result of the flood inventory map is displayed in Fig. 6.

The ROC curve reflects the ability to distinguish positive and negative instances, in which the basis of the assessment is the true-positive and false-positive rates. By applying various threshold values and calculating the corresponding points in the ROC space, the flood risk map generated by the AHP model for the combination of different flood parameters is calculated with the corresponding AUC obtained. Figure 7 depicts the output for the ROC curve plot for the true positive rate (sensitivity) against the false positive rate (1-specificity) for all cut-off values. The smallest cut-off value is the minimum observed test value minus 1, and the largest cut-off value is the maximum observed tested value plus 1. All the other cut-off values are the averages of two consecutive ordered observed test values.

AUC values close to 1.0 indicate a higher precision and reliability of the model. In the case of the prediction curve, the AHP model displayed a goodness-of-fit with an AUC value of 0.916 (91.6%) and a standard error of 0.018. The high AUC value implies that, with the existing conditions in the study area, the AHP model could predict flood occurrences and efficiently distinguish between areas within very high to very low flood risk classes without any bias. This result indicates an excellent correlation between the predicted flood risk map and the ground truth data. Similar findings of the present study dovetail with
findings of previous studies carried by Bouamrane et al., (2020); Khosravi et al., (2016); Saha and Agrawal, (2020) and Vojtek et al., (2021).

## 4 Conclusions

The present study focused on a GIS-Based Multi-Criteria Decision Modelling technique to analyse and predict urban flood risk within the Accra Metropolis. This technique was identified particularly based on its suitability for data-scarce environments, where the application of hydraulic models and machine learning methods are challenging. The proposed AHP model adopted five relevant flood contributing factors by calculating the weight of each parameter through a normalisation method to map flood risk of four previous flood years; 2007, 2010, 2015, and 2020 within the GIS platform. The model results showed five indices of flood hazards, with higher grades indicating areas more vulnerable to flooding. Empirical evidence from the variation in the distribution of flood risks over the last one and a half-decade revealed an upsurge in high flood risk areas. Over 60% of these identified areas are concentrated in the central, southern, eastern and western regions where high urbanisation level, dense buildings (slums), extensive impervious surfaces and low terrain is evident.

The ROC curve measured the performance of the AHP model plotted from prediction and observation, which showed an excellent AUC value of 0.916 (91.6%). This indication confirmed that the model was reliable according to the historical flood records and better fitted specifically for distinguishing the very-low to the very-high flood risk areas of the present study. The framework provides a feasible method to facilitate flood mitigation strategies in the Accra Metropolis. This approach is also applicable to other urban settlements of similar settings. However, this study recommends that further studies could focus on GIS-based Artificial Neural Network (ANN) modelling to simulate and predict flood in the Metropolis with acceptable accuracy. Integration of the model with a real-time warning system will provide a significant advantage to reduce flood damages significantly.

## Declarations

### Funding:
The author first received funding from the Ghana Government through the World Bank under the Africa Centres of Excellence project.

### Ethics approval:
The authors declare that the submitted manuscript is original. Authors also acknowledge that the current research has been conducted ethically and the final shape of the research has been agreed upon by all authors. Authors declare that this manuscript does not involve researching about humans or animals.

### Conflicts of interest/Competing interests:
The authors declare no conflicts of interests/ competing interests.

### Availability of data and material:
All data used in the study will be readily available to the public upon request.
**Code availability** (software application or custom code): All software applications used in this study were the licensed software applications used by the University of Energy and Natural Resource, Sunyani, Ghana.

**Consent to participate:** The authors consent to participate in this research study.

**Consent to publish:** The authors consent to publish the current research in Stochastic Environmental Research and Risk Assessment.

**Author contributions**

**Raymond Seyeram Nkonu:** Conceptualization, Resources, Methodology, Formal analysis and investigation, Writing - original draft preparation, Writing - review and editing. **Mary Antwi:** Supervision. **Mark Amo-Boateng:** Supervision. **Benjamin Wullobayi Dekongmen:** Review and editing.

**References**

https://databasin.org/datasets/862ea8a8de8c46029893147dba2ee287/


Figures
Figure 1

Study area map of Accra Metropolis
Figure 2

Overall methodology flowchart (Source: Author’s construct)
Figure 3

Classified LULC patterns in four different phases; 2007, 2010, 2015 and 2020
Figure 4

Thematic map of flood contributing parameters
Figure 5

Figure 6

Flood inventory map with flood inundation test locations
Figure 7

ROC curve for quantitative validation