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Mapping the impacts of recurrent floods and windstorms in Bauchi, Nigeria: a hybrid multi-criteria approach using fuzzy-AHP

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This study explores the spatial distribution and severity of Weather and Climate Extreme Events (WCEE) in Bauchi city, Nigeria, with a particular focus on flood and windstorm disasters from 2018 to 2023. Using a GPS device, the study identified and recorded the location of 1,236 buildings and structures affected by windstorms and 526 buildings and areas affected by annual floods. Through the utilization of decision-making analytical techniques such as Fuzzy Analytic Hierarchy Process (AHP) and Inverse Distance Weighting (IDW) spatial interpolation techniques, the study assesses patterns, severity, and exposure impacts of WCEE in Bauchi. The findings reveal significant disparities in the impacts of flood and windstorm hazards across different neighborhoods, with certain areas experiencing more severe impacts. The pattern shows that areas with inadequate drainage infrastructure or where residential buildings encroach upon water channels experience severe flood impact, while organic settlements characterized by compact housing, dense population, and non-compliant buildings within the traditional city and suburban areas are more impacted by windstorm disaster. This study further emphasized the strong connection between urban planning and urban disaster vulnerability, risk, and exposure and underscores the urgent need to integrate the ground realities of present and past disaster- and hazard-prone areas in Bauchi with spatial planning initiatives. Through collaborative efforts among planners, policymakers, and stakeholders to co-design and implement effective planning and disaster risk reduction solutions, the city's resilience to future WCEE can be enhanced.

KEYWORDS
hotspot mapping, geospatial technique, extreme events, disaster, Africa, vulnerability, exposure

1 Introduction

Weather and climate extreme events (WCEE) pose significant global challenge for both society and ecosystems, leading to profound impacts on lives and substantial economic losses annually (Bănică et al., 2020; Christian et al., 2019; Hussain et al., 2020; Kafi et al., 2024; Peden et al., 2023; Tang, 2019; Tran and Wilson, 2020). Notably, flooding, windstorms, droughts, and heatwaves emerge as prominent global climate hazards, each carrying significant and varied consequences in terms of loss and damage impacts (Dang, 2022; Gautam et al., 2020; Mera, 2018; Zhang et al., 2022). In recent times, several studies have reported how both countries of global north and south are hit hard by high-profile disasters from WCEE (Aitsi-Selmi et al., 2016; Feuerstein et al., 2011; Zou et al., 2023).

More than 11,000 incidents of extreme weather and climate events occurred between 1996 and 2017, resulting in more than 52,800 fatalities and economic losses of approximately US $3.08 trillion (Kreft et al., 2017). For example, flooding, windstorms, droughts, and heatwaves stand out as significant global climate hazards, each wielding profound and diverse loss and damage impacts (Boyd et al., 2021; Dang, 2022; Jackson, 2023; Mera, 2018; Zhang et al., 2022). These hazards transcend international borders, inflicting considerable economic, environmental, and social losses on nations irrespective of their developmental status (Birkmann et al., 2022; Martinez-Diaz et al., 2019; Rentschler et al., 2022). Floods, characterized by their ability to inundate regions, have resulted in more casualties and economic losses of over $80 billion in 2016 alone, outdoing all other natural disasters documented in recent decades (Jongman et al., 2012; Kemter et al., 2020; Mohammed, 2019). Furthermore, windstorms are another serious weather- and climate-related disaster ravaging Europe and Africa (Gregow et al., 2017; Hernandez et al., 2020; Jahani and Saffariha, 2021; Osuteye et al., 2017), growing in intensity due to warming oceans, amplifying structural and infrastructural damage, causing financial setbacks, and social disruption (Gaska, 2023; Kopp et al., 2017; Sethunadh et al., 2023). Because of changes in meteorological parameters and continued tree cutting, the trend is expected to increase in frequency, intensity, and impact, particularly in Africa (Barau et al., 2023a; Gardiner, 2021; Kafi and Ponrahono, 2026). Unlike in Europe, where data repositories and observatories are abundant, inadequate data remains the biggest challenge for planners and policymakers in Africa to effectively undertake risk reduction measures (Osuteye et al., 2017).

Although the evidence-based connection between cities, urban planning, disaster vulnerability, exposure and risk reduction has been established (Aqib et al., 2020; Bertilsson et al., 2019; Cui et al., 2019), relatively few studies have explored the impact of spatial planning and urban form on disaster risk, exposure, and severity (Kafi and Ponrahono, 2025). Globally, climate change and urbanization are recognized as key factors exacerbating disaster risks, exposing cities in both developed and developing nations to increased impacts of weather and climate extreme events (Gaisie and Cobbinah, 2023). Recent studies emphasize how uncontrolled urbanization amplifies vulnerabilities and exposure to the severe consequences of WCEE (Kafi et al., 2021; Kron et al., 2019; Saghir and Santoro, 2018; Tate et al., 2021). As a result, UN-Habitat emphasizes the crucial role of urban planning in disaster governance, environmental sustainability, and city and climate resilience. Additionally, the United Nations' New Urban Agenda underscores the urgent need to integrate disaster risk reduction (DRR) and climate adaptation strategies into sustainable urban planning and climate-friendly city design (Lee et al., 2018).

The two most frequently recurring weather and climate extreme disasters of significant environmental, social, and economic consequence that devastate Nigerian cities are flooding and windstorms (Adelekan and Asiyanbi, 2016; Audu et al., 2013; Nkwunonwo et al., 2016; Shuaibu et al., 2022). These events have become recurrent, causing destruction to lives and properties in Nigerian cities, with Bauchi being among the worst-hit cities by these twin disasters (Kafi and Ponrahono, 2025). Over the last decade, Bauchi has witnessed more than 40 incidents of floods and windstorms of varying intensities and magnitudes (Kafi et al., 2025). Notably, the 2018 windstorm that destroyed more than five thousand infrastructure–houses, hospitals, schools, telecom mast, etc., and economic asset to the tune of $200 million (Kafi et al., 2019). Although the prevailing wind speed and degree of damage of the windstorm destruction are known (Kafi et al., 2021), the spatial pattern and its associated disproportionate impact across the city are yet to be known.

Therefore, examining the spatial pattern of windstorm impacts is essential for identifying highly affected neighborhoods, understanding variations in exposure and vulnerability, and determining the extent to which complex urban systems influence impact severity. Similarly, despite the recurrent incidence of flooding in the city and its associated impacts, including property destruction and population displacement, no previous study has simultaneously examined the spatial patterns, severity levels, and cumulative impacts of these twin disasters in Bauchi. A spatially explicit assessment is therefore necessary to map impact hotspots, quantify damage extent, and support targeted planning and disaster risk reduction interventions. Moreover, field based assessments of damaged infrastructure indicate that environmental loading conditions and local ground characteristics strongly influence infrastructure performance, underscoring the need for evidence based and spatially explicit frameworks when evaluating exposure and vulnerability (Ahmad et al., 2025a).

The application of analytical decision making and spatial interpolation techniques in WCEE studies has significantly advanced understanding of the multidimensional impacts of these hazards events (Ekmekcioğlu et al., 2021; Fung et al., 2022; Nayeri et al., 2022; Yang et al., 2013). Recent studies have demonstrated the growing role of these analytical frameworks in assessing infrastructure vulnerability under adverse ground and environmental conditions, emphasizing the value of integrating field data with quantitative evaluation methods to support risk-informed decision-making (Ahmad et al., 2025b). These techniques provide a robust, data driven framework for integrating multiple spatial data layers, thereby enabling the identification of causal factors, evaluation of vulnerability, assessment of risk, and quantification of impacts with a high level of reliability (Bertilsson et al., 2019; Bouramtane et al., 2021; Kahraman et al., 2015; Shuaibu et al., 2022). Within this context, multi criteria decision analysis (MCDA) techniques have proven particularly effective for disaster risk assessment, especially where complex decision making is required.

Consequently, numerous studies have employed MCDA methods such as the Analytic Hierarchy Process (AHP), TOPSIS, VIKOR, and Fuzzy logic to support disaster risk reduction initiatives. However, as noted by Kafi and Ponrahono (2024), these methods possess inherent limitations, prompting growing advocacy for hybrid approaches capable of addressing the shortcomings of individual techniques. In response, recent studies have applied hybrid MCDA methods such as fuzzy-AHP and fuzzy-TOPSIS, while others have integrated MCDA with machine learning to enhance disaster risk analysis (Costache et al., 2022; Khosravi et al., 2019). Notably, most of these applications focus on vulnerability or risk assessment, with very limited attention to disaster impact assessment, and no study to date

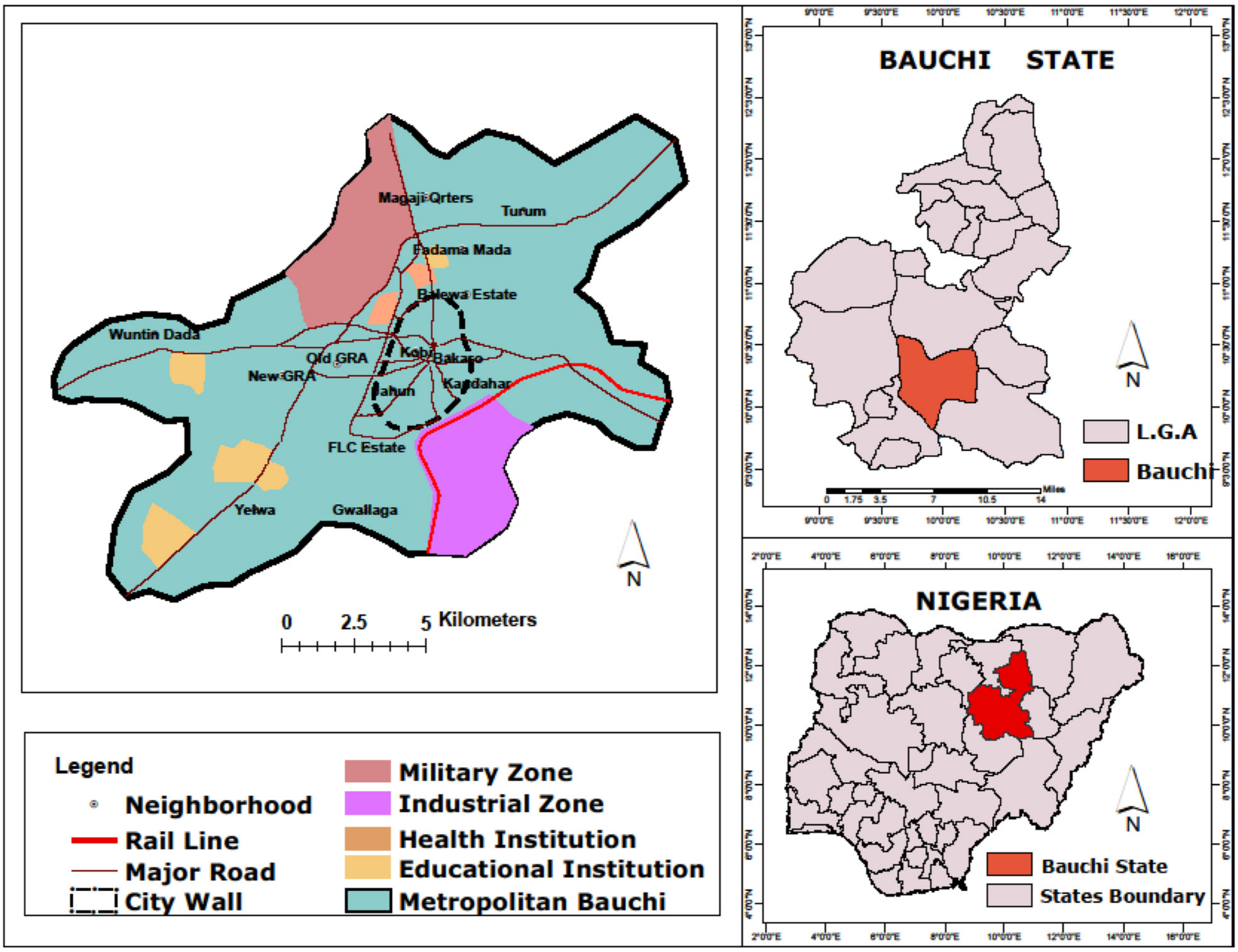

FIGURE 1
The study area.

has applied hybrid MCDA approaches to map the compounded impacts of multiple disasters. Building on this gap, the present study adopts a novel multi method framework to map and assess recurrent flood and windstorm impacts in Bauchi metropolis. Specifically, the study utilized locational data of affected areas, buildings, and structures, applied the Fujita scale for damage rating, and integrated Fuzzy logic and AHP based MCDA (fuzzy-AHP) with Inverse Distance Weighting (IDW) spatial interpolation to delineate spatial patterns and identify impact hotspots of the two most recurrent weather and climate extreme events in Bauchi.

2 Materials and methods

2.1 Study area

Bauchi, the capital of Bauchi state is situated approximately between latitudes 9° and 12° North and longitudes 8° and 11° East (Sadiq et al., 2014). It shares borders with several neighboring states (See Figure 1), including Kano to the northwest, Jigawa to the north, Yobe to the northeast, Gombe to the east, Taraba to the southeast, and Plateau to the west (Kafi et al., 2014). The city's population is estimated to be over 500,000 people, making it one of the most populous states in Nigeria (Kafi et al., 2019). Bauchi State covers a land area of approximately 49,119 square kilometers, encompassing diverse geographical features ranging from the Sudan Savannah in the north to the Guinea Savannah in the south (Sadiq et al., 2014).

Climatically, Bauchi State experiences a tropical climate characterized by distinct wet and dry seasons (Kafi et al., 2014). The wet season typically lasts from May to October, with heavy rainfall occurring during this period. The dry season, on the other hand, extends from November to April, characterized by hot and dry weather conditions (Kafi and Ponrahono, 2025). The state's climatic variability influences various socio-economic activities, including agriculture, trade, and livestock rearing. Agriculture is a significant economic activity in Bauchi State, with crops such as maize, millet, sorghum, rice, and vegetables being cultivated. Livestock farming, particularly cattle, sheep, and goats, also plays a crucial role in the state's economy.

2.2 Data collection

2.2.1 Flood and windstorm Inventory

To undertake data collection, first, a WhatsApp group was established, comprising residents from diverse neighborhoods within Bauchi. The group is composed of 25 members, predominantly youth and middle-aged men who have resided in Bauchi for over 15 years. They represent diverse educational and professional backgrounds, including university lecturers, healthcare professionals, civil society organization members, and business owners. This diverse representation provided useful local knowledge and perspectives on disaster-prone areas, The primary objective and purpose of the study were communicated to the group members to solicit their full support and participation in identifying flood-affected areas. However, given the catastrophic nature of the 2018 windstorm, which affected virtually all neighborhoods, an extensive tour of all areas was conducted to identify affected buildings and structures. During the survey, Ward heads and youth volunteers were engaged to assist with gathering useful information and providing firsthand insights into the areas impacted by these events (Kafi et al., 2021). This collaborative approach facilitated the comprehensive identification of flood-prone zones and windstorm-affected buildings and structures in the study.

The study utilized GPS devices to record location coordinates of areas, buildings, and structures with a history of flood and windstorm damage (Kafi and Gibril, 2016; Tempa and Yuden, 2023) (see Figure 2). Through a comprehensive census, all areas, buildings, and structures affected by flooding or windstorms between 2018 and 2023 were recorded with their accompanying damage information (Kafi et al., 2021). A total of 526 flood points affecting buildings, structures, and areas, as well as 2326 cases of windstorm destruction to buildings and structures, were recorded during the field survey (See Figure 3). Additionally, coordinates of non-flooded areas were recorded to accurately identify flood impact hotspots (Bouramtane et al., 2021).

2.2.2 Data reliability

The enumeration exercise was largely comprehensive and reliable, as reported areas and buildings were verified through multiple methods (Kafi et al., 2021): i) visual observations of impacts such as water lines on walls, dampness, cracks or damaged walls, roofs, and structures; ii) corroboration by neighbors, community leaders, and ward heads; and iii) photographs provided by some affected residents. However, certain limitations existed. Some areas, including military formations, a few public institutions, and buildings of residents who denied access due to perceived political motives, could not be directly surveyed. To mitigate omissions, some of the inaccessible areas were recorded using Google Earth, supplemented with available information on observed damage.

2.3 Impact assessment

2.3.1 WCEE intensity ranking

To assess the impact of weather and climate extreme events such as windstorms and flooding, the study adopted the damage ranking conducted by Kafi et al. (2021) using the Fujita scale for windstorm damage rating (See Figure 4). The EF-scale is a tool for rating and ranking windstorm and tornado destruction based on estimated windspeed at the time of the disaster event (Godfrey and Peterson, 2017). This tool has been widely adopted in windstorm rating because it accounts for various types of building materials and components across the damage spectrum (Gautam et al., 2020; NOAA, 2011). Similarly, the tool has been widely reported to be promising in estimating the prevailing wind speed of windstorm destructions (Edwards et al., 2021; Groenemeijer et al., 2023). Conversely, the study ranked flood severity based on flood victims' lived experiences and their history of flood occurrences since there is no universal scale or guideline for rating flood damage (Ahmad Bukhari and Hassan Rizvi, 2015; Ajibade et al., 2013). Although this approach may introduce recall bias among respondents, it is justified by the scarcity of long-term flood records in the study area (Kafi et al., 2025). Additionally, several studies have successfully employed community-based lived experiences in flood assessments under data-scarce conditions (Ahmad Bukhari and Hassan Rizvi, 2015; Singh, 2020; Udo and Naidu, 2023), demonstrating their relevance for capturing undocumented flood histories. This ranking relied on three key impact factors: flood frequency, extent, and severity.

2.3.2 WCEE mapping

To understand the pattern and dimensionality of impacts resulting from WCEE, the study executed spatial interpolation to produce six distinct hotspot maps reflecting various pattern, types and severity of effects caused by windstorms and floods throughout the study period (Paradilaga et al., 2021; Tate et al., 2021). These hotspot maps were generated using the IDW interpolation technique within a Geographic Information System (GIS) environment. This technique was selected for its computational efficiency and effectiveness in estimating values at unknown locations and interpolating point data (Barau et al., 2023b; Fung et al., 2022). Additionally, numerous comparative studies on the suitability of geospatial techniques reveal that IDW is often more accurate and effective especially scattered phenomenon (Achilleos, 2008; Kafi and Ponrahono, 2024), as demonstrated by its superior performance (Fung et al., 2022; Paradilaga et al., 2021). This superiority can be attributed to IDW's consideration of the inverse relationship between distance and influence, making it particularly suitable for situations where nearby points exert a stronger influence on the interpolated values than those farther away (Al-Mamoori et al., 2021).

There are quite many equations that explains the principle behind IDW, but the most commonly used formula is the Shepard method (Azpurua and Ramos, 2010), which assign a weight function denoted as w_i and defined as below (see Equation 1);

$$w_i = \frac{\left[h_j^{(-p)}\right]}{\left[\sum_{i=0}^{n} h_j^{(-p)}\right]} \tag{1}$$

Where, p signifies a positive real number referred to as the power parameter, conventionally set at $p = 2$. Additionally, h_j denotes the distance between interpolated point and the dispersion point,

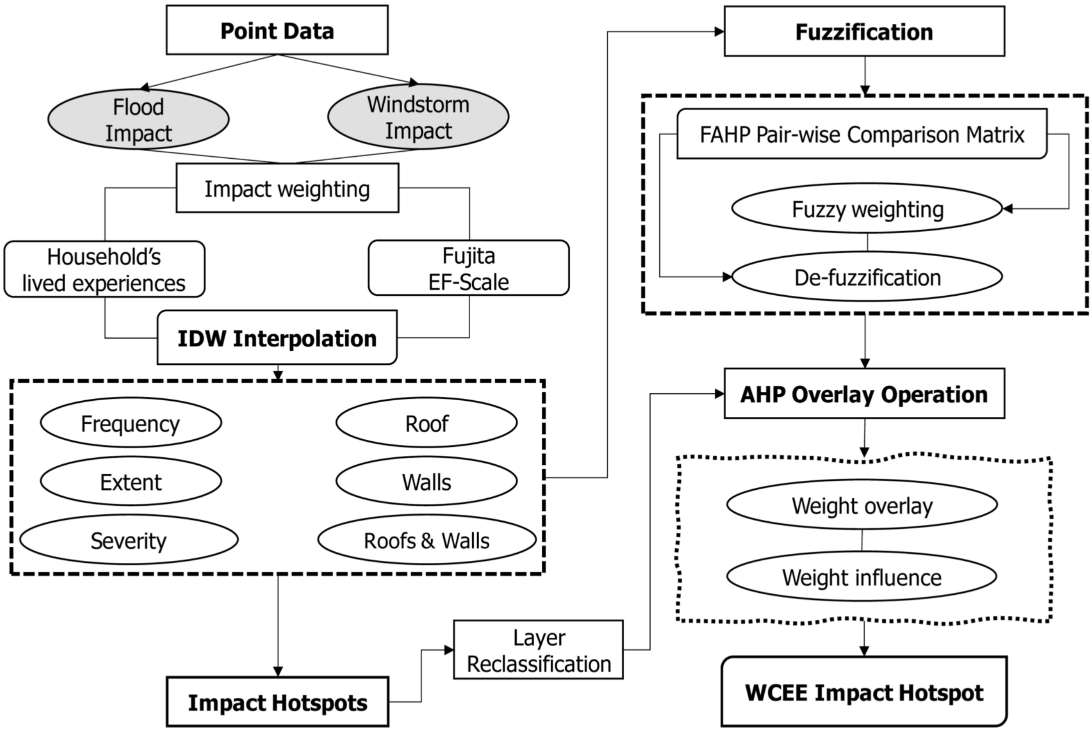

FIGURE 2
Methodological flowchart for WCEE impact assessment.

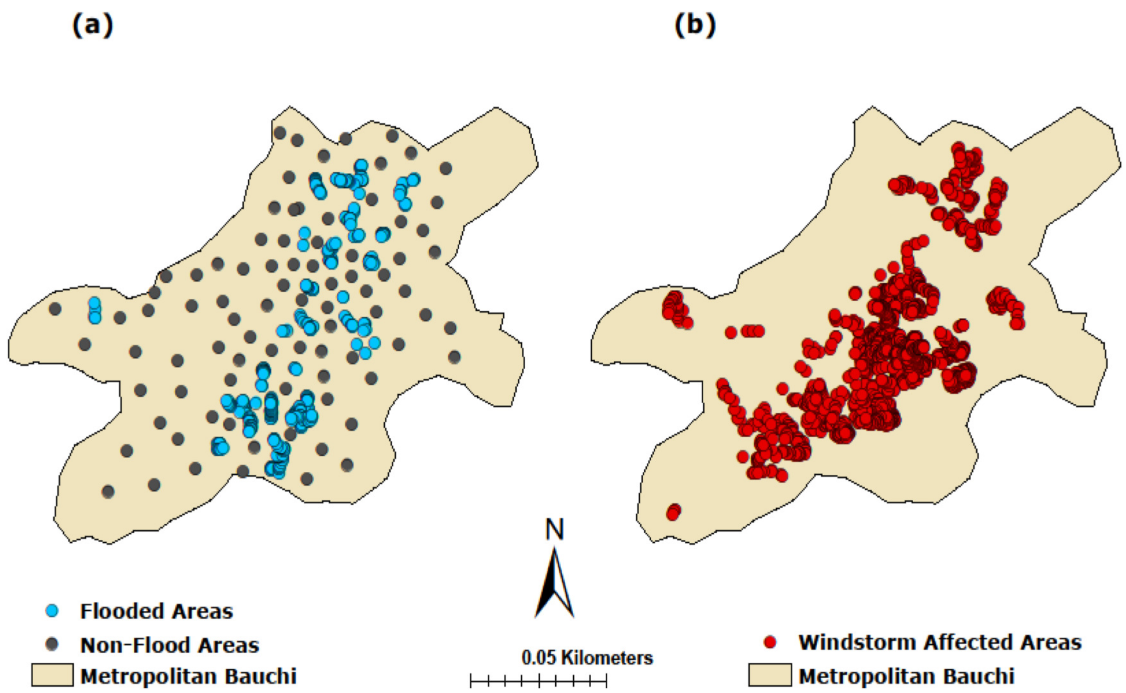

FIGURE 3
Historical GPS points showing **(a)** the distribution of areas affected by floods and **(b)** areas affected by windstorm events across the study area.

	Fujita damage class	f0	f1	f2	f3	f4	f5
	Loss ratio (%)	0.1	1	10	50	90	100
	Degree of damage → **Damage indicator** ↓	Light roof damage	Significant roof damage	Roof gone	Walls partly collapsed	Largely blown down	Blown away
A	Weakest Outbuilding	F0+ 0	F0+ 0	F1- 0	F1- 0	F1+ 0	F2- 0
B	Outbuilding	F0+	F1- 0	F1+ 0	F2- 102	F2+ 69	F3- 33
C	Strong outbuilding	F0+ 15	F1+ 7	F2- 3	F3- 196	F3+ 89	F4- 22
D	Weak brick structure	F1- 346	F1+ 230	F2+ 114	F3+ 314	F4- 190	F5 44
E	Strong brick structure	F1- 254	F2- 108	F3- 60	F4- 37	F5 29	F5 10
F	Concrete Building	F1- 43	F2+ 11	F3+ -	F4+ -	F5 -	F5 -
	Total	658	356	177	649	377	2326

FIGURE 4
The degree of damage ranking for 2018 Bauchi windstorm destruction based on Enhance Fujita scale (EF-scale). Adopted from Kafi et al. (2021).

determined through the equation:

$$h_i = \sqrt{(x - x_i)^2 + (y - y_i)^2} \tag{2}$$

As depicted in the above Equation 2, the values (x, y) denote the estimated (interpolated) coordinates of each unknown point, while (x_i, y_i) denotes the coordinates of each dispersion point.

2.3.3 Multicriteria decision analysis

To evaluate the overall impact of WCEE in the study area, the study uses the multicriteria decision analysis approach (Kafi and Ponrahono, 2024). The MCDA is widely utilized due to its diverse applicability and suitability for making informed decisions based on multicriteria analysis (Daksiya et al., 2017; Rana et al., 2022; Więckowski and Dobryakova, 2021). Employing the MCDA approach in Disaster Risk Reduction (DRR) studies, especially those focusing on comprehensively evaluating the impact of WCEE, is crucial. It facilitates the assessment of complex decision-making scenarios and aids in identifying areas with the highest multidimensional impact (Elma et al., 2024; Shuaibu et al., 2022). Therefore, this approach was chosen because it enables the integration of various factors (hotspot maps) for a comprehensive evaluation of the multidimensional nature of the impacts of these events over time (An et al., 2020; Kahraman et al., 2015; Olatunji et al., 2023).

2.3.3.1 Weightage criteria

The weighting criteria involve four different steps. Criteria identification, pairwise comparison, fuzzy membership function, and defuzzification (Kahraman et al., 2015; Suganthi et al., 2015).

The first step involves determining the key factors that are essential for assessing the impact of WCEE in the study area. Six WCEE hotspot maps, three derived from windstorm destruction and three from past flood exposure, were considered essential criteria based on their severity, dimensionality, and relevance in understanding the overall impact of WCEE (see Figures 7, 8). These criteria include flood frequency (F_f), flood extent (F_e), flood severity (F_s), roof damage (R_d), wall damage (W_d), and roof and wall damage (B_d) (See Table 2).

Fuzzy-AHP pairwise comparison method was employed to determine the relative importance of these criteria. While, various fuzzy-AHP approaches have been employed by different researcher (Hadipour et al., 2020), the study utilized the fuzzy-AHP procedure developed by (Deng, 1999) because it uses a combination of fuzzy membership and AHP pairwise comparison matrix to assess the relative importance of WCEE impact indicator. Additionally, this technique overcomes the limitation of AHP - crisp pairwise comparison by fuzzifying the AHP crisp into a fuzzy number as shown in Table 1. It also allows for the representation of uncertainty and imprecision inherent in the pairwise comparisons, ensuring a thorough assessment of the criteria's relative importance (Deng, 1999; Yang et al., 2013).

$$(A = (a_{ij}) = \begin{pmatrix} (a_{1l}\,a_{1m}\,a_{1u})(a_{2l}\,a_{2m}\,a_{2u}) & \cdots & (a_{n1l}\,a_{n2m}\,a_{n3u}) \\ (a_{2l}\,a_{2m}\,a_{2u})(a_{2l}\,a_{2m}\,a_{2u}) & \cdots & (a_{n2l}\,a_{n2m}\,a_{n2u}) \\ \vdots \quad \vdots & \vdots & \vdots \\ (a_{m1l}\,a_{m1m}\,a_{1u})(a_{m2l}\,a_{m2m}\,a_{2u}) & \cdots & (a_{mn1l}\,a_{mn2m}\,a_{mn2u}) \end{pmatrix} \tag{3}$$

TABLE 1 **Linguistic scale and corresponding Fuzzy and AHP values.**

Linguistic variables	Crips AHP numbers	Reciprocal of crips AHP number	TFN	Reciprocal of TFN
Equally important	1	1	(1,1,1)	(1,1,1)
	2	1/2	(1,2,3)	(1/3, 1/2, 1/1)
Moderately important	3	1/3	(2,3,4)	(1/4, 1/3, 1/2)
	4	1/4	(3,4,5)	(1/5, 1/4, 1/3)
Strongly important	5	1/5	(4,5,6)	(1/6, 1/5, 1/4)
	6	1/6	(5,6,7)	(1/7, 1/6, 1/5)
Very strongly important	7	1/7	(6,7,8)	(1/8, 1/7, 1/6)
	8	1/8	(7,8,9)	(1/9, 1/8, 1/7)
Extremely important	9	1/9	(9,9,9)	(1/9, 1/9, 1/9)

Numbers 2, 4, 6, 8 are intermediate preference between adjacent scales.

The fuzzification process was developed through a collaborative approach involving 12 experts in Environment, Urban Planning, and Geography, each with over 10 years of teaching experience and specialized background in disaster risk reduction (Hoque et al., 2024). To capture and combine their assessments systematically, expert judgments were aggregated using the arithmetic mean method, providing a consensus-based and robust representation of the relative importance of each criterion. This approach ensured that the fuzzified values reflected both expert knowledge and collective agreement, enhancing the reliability of subsequent analyses.

The fuzzification process was established through a collaborative process involving 10 experts from the fields of Environment, Urban Planning, and Geography who are specialist in the field of disaster risk reduction ensuring a thorough consideration of all the hotspot maps and their magnitude of impact in comparison to one another (Dadras et al., 2014; Darabi et al., 2019). It serves as the initial step in computing the fuzzy scale weight and plays a pivotal role in managing vague and subjective judgement on the factors relative importance (Ahmadi and Ebrahimi, 2019; Dadras et al., 2014; Gumus et al., 2016). The guidance of experts was instrumental in providing insights in assigning the fuzzy scale to each of the six factors, ensuring that the weighting reflects their relative importance in the pairwise comparison (Ebrahimian Ghajari et al., 2017). The fuzzy scale relative importance based on the TFN is computed using Equation 4 and integrated into an AHP pairwise comparison matrix as shown in Equation 3 (Ekmekcioğlu et al., 2021; Yang et al., 2013).

Fuzzy set A (for triangular numbers), denoted by $[\mu_A]$, have their numbership functions defined by the mathematical equations as follows (Nayeri et al., 2022; Nguyen et al., 2021; Wang, 2015).

$$\mu_A = \begin{cases} \dfrac{x - a_l}{a_m - a_u}, a_l \leq x \leq a_m \\ \dfrac{a_u - x}{a_u - a_m}, a_l \leq x \leq a_m \\ o, \end{cases} \quad (4)$$

The triangular fuzzy set A as shown in Figure 5 is denoted by a triplet $(a_{l,} a_{m,} a_u)$, Equation 4.

After computing the weightage result based on the fuzzy-AHP criteria, the fuzzy weight $(a_{l,} a_{m,} a_u)$ were then converted into crisp numbers through the process of defuzzification (Hong et al., 2018; Kahraman et al., 2015). The aim of the defuzzification is to obtain a crips, well-defined numerical values which represent the weight $[w_i]$ of each of the conditioning factors that are going to participate in the fuzzy or AHP weight overlay. The process is done by calculating the mean of the fuzzy weight criteria as shown in Equation 5 (Nguyen et al., 2021).

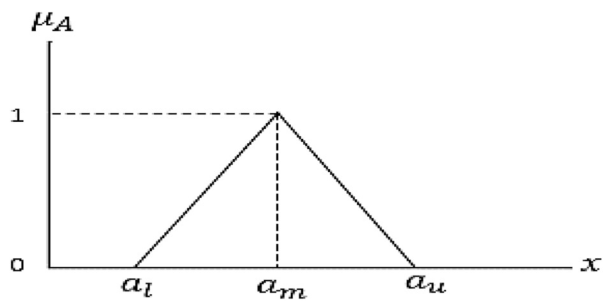

FIGURE 5
Showing the schematic diagrams of (a) triangular fuzzy numbers numbers, given by A = $\{a_{l,} a_{m,} a_u\}$.

$$w_i = \frac{a_1(+)a_2(+)\ldots a_n}{n} \quad (5)$$

Pairwise comparisons were conducted using a Matrix and fuzzy Crips Weight Based on TFN (see Tabel 2), weight and consistency ratios were calculated to ensure the reliability of expert judgments, with values below the acceptable threshold indicating acceptable consistency (Kafi and Ponrahono, 2024; Yang et al., 2013). The validated pairwise comparison matrices were then aggregated to derive final weights for the analysis (See Table 3).

The WCEE conditioning parameters were processed in ArcMap 10.8, where the Weighted Sum Overlay Tool was applied to generate the WCEE impact hotspot map. The assigned weights reflect the functioning of the fuzzy-AHP approach (Table 2). According to Dadras et al. (2014), the consistency ratio is calculated as the ratio of the consistency index to the average consistency index derived from a large sample of randomly generated matrices (Table 3).

TABLE 2 Pairwise comparison matrix and fuzzy crips weight based on TFN.

F	F_f			F_e			F_s			R_d			W_d			B_d		
F_f	1	1	1	0.25	0.33	0.50	0.13	0.14	0.17	0.17	0.20	0.25	0.13	0.14	0.17	0.11	0.11	0.11
F_e	2	3	4	1	1	1	0.17	0.20	0.25	0.25	0.33	0.50	0.13	0.14	0.17	0.13	0.14	0.17
F_s	6	7	8	4	5	6	1	1	1	2	3	4	0.33	0.50	1.00	0.20	0.25	0.33
R_d	4	5	6	2	3	4	0.25	0.33	0.50	1	1	1	0.25	0.33	0.50	0.17	0.20	0.25
W_d	6	7	8	4	5	6	1	2	3	2	3	4	1	1	1	0.25	0.33	0.50
B_d	9	9	9	6	7	8	3	4	5	4	5	6	2	3	4	1	1	1

F_f, Flood frequency; F_e, Flood extent; F_s, Flood severity; R_d, Roof damage; W_d, Walls damage; B_d, Roof and wall damage.

TABLE 3 Fuzzy-AHP weight and consistency values.

Contributing parameters	Fuzzy-AHP weight (Wi)	Consistency (%)
Flood frequency (Ff)	0.03	3
Flood extent (Fe)	0.05	5
Flood severity (Fs)	0.17	17
Roof damage (Rd)	0.09	9
Wall damage (Wd)	0.22	22
Roof and wall damage (Bd)	0.44	44
Total	1	100

2.3.4 WCEE impact hotspot

The impact mapping process in this study involved several key steps. Firstly, six hotspot maps were generated based on various dimensions of flood and windstorm damage as stated earlier (Tempa and Yuden, 2023). Specifically, three maps depicted windstorm destruction pattern on roofs, walls, and both roofs and walls. The other three maps were based on flood effects and exposure pattern, focusing on frequency, extent and severity of flooding (see Figures 7, 8).

To generate the impact map, the AHP overlay operation within a GIS was employed (Chukwu et al., 2023; Hoque et al., 2019). This method allows for the integration of the six hotspot maps and assigning weight (percentage of influence) to each of the participating maps to produce a comprehensive map of the overall impact of WCEE in the study area (Abdrabo et al., 2020; Choubin et al., 2019). The weight of each hotspot map was computed based on the percentage of influence calculated using fuzzy-AHP weighting. This allowed for the consideration of the relative importance of each map in contributing to the overall impact assessment. By incorporating fuzzy-AHP weights, the analysis accounted for uncertainties and subjective assessments, enhancing the objectivity and accuracy of the impact mapping results (Costa et al., 2023; Gumus et al., 2016; Yang et al., 2013).

3 Results

For the purpose of this study, 5 years of historical floods and windstorm data were aggregated due to the limited and disproportionate number of extreme events per year, particularly for windstorms, where the most destructive event occurred in 2018 with over 2,300 destructions and the next in 2023 with about 70 cases of destructions. Although floods occur annually in Bauchi, to ensure consistency and robust analysis across hazard types, both windstorm and flood events were analyzed using multi-year aggregated data.

3.1 Flood impact and severity pattern

3.1.1 Flood frequency

The study findings concerning flood Frequency uncovers an alarming trend of increasing flood incidences over the years. The study found that areas classified as "very high" experience seven or more flood incidents per year, those designated as "high" experience three to four incidents annually, areas with "moderate" flood severity experience at least one incident per year, those classified as "low" experience one incident every two to 3 years, while areas categorized as "very low" experience no flooding or at most one incident every four to 5 years. This concerning pattern is particularly evident in residential neighborhoods where numerous buildings encroach upon water channels without appropriate setbacks (Ganji et al., 2022; Li et al., 2022; Shuaibu et al., 2022). Specifically, neighborhoods such as Gwallagan Mayaka, Ungwan Duhu, Korama, Zango, Gidan Kaji, Fadaman Mada, and Bakin Kura have been identified as experiencing high frequencies of floods (see Figure 7a). These areas are highly vulnerable to recurrent flooding due to various factors, including their geographical landscape, lack of adequate drainage networks, encroachment practices, and building types and patterns.

A woman recounted how the constant threat of floods has left her and her family in a perpetual state of fear during the rainy season, especially when it rains at night. She described the overwhelming stress of spending countless nights evacuating floodwater from their home and trying to save their belongings from damage. She further expressed a willingness to sacrifice her home if it meant creating a proper drainage system to save the Fadaman Mada community from incessant floods.

3.1.2 Flood extent

The flood extent assessment focuses on determining the spatial reach of floods in the study area. Some pictures of areas with recurrent flood incidences in the study area are shown in Figures 6a–h. Areas inundated by floodwaters covering 50 m or more are categorized as high and very high flood extents. Additionally, flood extent includes flood depth, where depths exceeding 1 m in height are considered very high (see Figure 6f). Many residents faced with floodwaters exceeding 1 m in depth describe distressing encounters of water seeping into their homes through doors, windows, and other drainage outlets, instead of being directed away as intended. During the survey, one victim showed us how he had to erect a 1-m-high barrier around his door to prevent floodwater from inundating his house, highlighting the local coping measures residents take to protect their homes. Additionally, another resident recounted how floodwaters were seeping up from the ground and through water outlets, forcing them to immediately evacuate some of their belongings that were not yet destroyed by the floodwater.

Unlike flood frequency, which identifies over 8 different hotspot areas experiencing incessant flooding, the flood extent analysis reveals that only a few areas encounter very high flood inundations exceeding a radius of 60 m and or 1 m flood depth (see Figure 7b). Specifically, neighborhoods such as Gwallagan Mayaka, Korama, Bayan Kotu, and certain parts of Fadaman Mada are identified as experiencing very high flood extents. These areas share a common characteristic of buildings constructed either on waterways or abutting river channels (see Figures 6c,h). For example, Korama and some parts of Fadaman Mada have a notable number of buildings affected by floods due to construction on waterways, while Gwallan Mayaka features a significant number of buildings along the riverbank.

3.1.3 Flood severity

Flood severity encompasses various damages to buildings and properties caused by floodwaters, with areas experiencing high to very high severity facing significant destruction and emergencies necessitating relocation or displacement. Among the worst-hit areas are Bayan Kotu, Magaji Quarters, Korama, and Madina Quarters, where frequent flood damages lead to household displacement and occasional fatalities annually (see Figure 7c). For instance, in Magaji Quarters, a female victim described how her house was inundated in 2022, resulting in extensive damage and displacement as belongings were swept away into a nearby gully. Similarly, in Bayan Kotu, female residents express constant panic during rainy seasons due to frequent and severe inundations which often leads to the destruction of properties. These firsthand testimonies underscore the profound impact of floods, particularly on vulnerable groups like women and children. Furthermore, the severity of flood impacts in these neighborhoods highlights the urgent need for effective flood risk management measures.

In contrast to other severely affected areas where encroachment and building on waterways contribute to flood severity, Madina Quarters faces challenges due to the absence of a drainage network. Additionally, a major water outlet collecting runoff water from nearby neighborhoods exacerbates the situation by spreading floodwaters and causing severe damage. This disparity in flood severity underscores the importance of addressing infrastructure deficiencies, such as the lack of drainage systems, to mitigate flood risks effectively. By implementing measures to improve drainage infrastructure and regulate development in flood-prone areas, policymakers can enhance resilience and reduce the adverse impacts of floods on vulnerable communities.

3.2 Windstorm impact and severity pattern

3.2.1 Roof damage

The assessment of windstorm roof damage is based on a rating system that ranges from slightly damaged (very low) to roof gone (very high), derived from the EF scale rating (Stewart et al., 2016). The findings reveal that building roofs are the most affected by windstorm disasters, with damage severity predominantly falling within the “moderate to high” ranking (see Figure 8a). The pattern of destruction indicates that the most affected neighborhoods are those within the traditional settlements of Bauchi (inner city) and the suburban settlements such as Turum, Lushi, Zango, Yelwa, and Kandahar. These areas exhibit similar morphological and physical planning patterns characterized by compact and low-quality residential buildings usually constructed with cement and mud motar (Gautam et al., 2020; Kafi et al., 2021). Within the inner-city traditional settlements, Bakaro and Karofi are the worst-hit areas by windstorms, with more than 70 houses having their roofs completely gone and many others suffering significant damage (see Figure 8a). A victim of the windstorm in Karofi vividly recounted how the rooftop of his house was completely blown off and carried more than 150 m away by the sheer force and pressure of the windstorm. Similarly, within the suburban settlements, neighborhoods like Lushi, Kandahar, and Turwun have witnessed a significant number of high roof-related impacts, including many incidents of blown-off roofs.

3.2.2 Walls damage

Similar to roof damage, the severity of wall damage was rated using the Fujita EF-scale, with ratings ranging from partial damage (very low) to blown away (very high). The findings reveal

FIGURE 6
(a) An institutional building had its roof completely blown off by windstorm. **(b)** A newly built pavilion had its walls and roof partially damaged by the 2023 windstorm. **(c)** Commercial development encroaching on a water way along Federal Low-cost Bye-pass. **(d)** A residential building significantly damaged by the 2018 windstorm. **(e)** An access road in Fadaman Mada area completely inundated by flood water. **(f)** An area in Federal Low-cost bye-pass inundated by flood water above 1 m deep. **(g)** A two-block barrier erected around entrance gate to prevent floodwater from inundating the building in. **(h)** Residential buildings in Fadaman Mada area constructed along waterways obstruct the natural flow of water, increasing the risk of severe flooding.

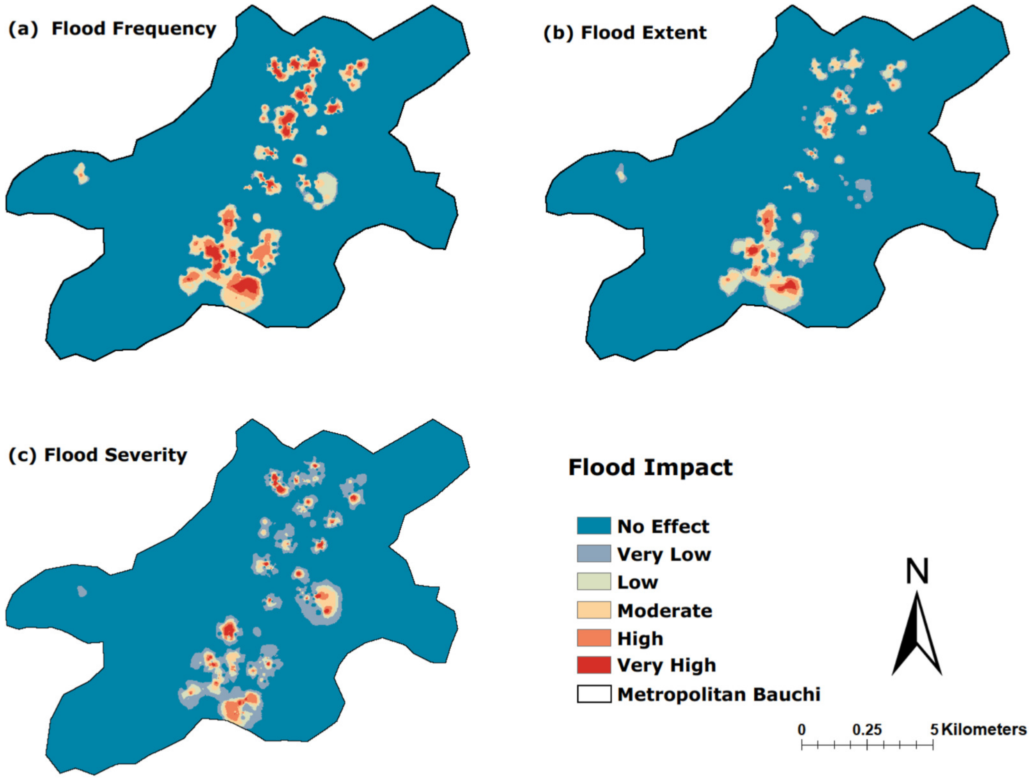

FIGURE 7
Flood hotspot maps showing impact severity pattern based on victims' lived experiences and history of occurrences **(a)** frequency, **(b)** spatial extent and **(c)** impact severity.

that damage to building walls alone is the least impactful aspect of windstorm destruction (See Figure 8b). Although some areas, such as Ungwan Makafi, Tirwun, Wuntin Dada, and Kandahar, experienced moderate to high impacts of windstorm destruction to walls, most affected buildings are ranked between low and very low impact levels.

The pattern of impact shows a concentration of damage incidents within the traditional settlements of the inner city, including neighborhoods like Zango, Gwallangan Mayaka, Lush, Yelwa, Bayan Airport, and Wuntin Dada. Although the severity of impact on individual buildings is generally low, the spatial coverage is wider, suggesting that more neighborhoods are affected by these incidents (See Figure 8b).

The only neighborhood with damage severity ranked as "very high" is Bayan Airport. This can be attributed to the fact that the area is newly developed, with most of the buildings under construction during the incidents and pockets of trees contributing to the severity of the damage.

3.2.3 Damage to roof and walls

Damage to roof and walls assessed a condition where both the vertical (roofs) and horizontal (walls) components of buildings and structures are impacted by windstorms at varying degrees. The severity of damage is ranked similarly to other forms of windstorm destruction, using the EF-scale. Damage ranges from partly destroyed (very low) to completely destroyed (very high), allowing for a comprehensive evaluation of the extent of destruction caused by the windstorm. The findings from the study indicate that damage to both roofs and walls represents the most severe form of destruction caused by the windstorm (See Figure 8c). It was observed during the survey that many buildings suffered damage to both their vertical and horizontal components, underscoring the extensive nature of the destruction.

Analysis of the hotspot pattern revealed significant spatial extent of the areas affected, ranked with "high" severity. However, areas such as Bakin Kura, Karofi, Kofar Dumi, Malan Goje, Sabuwar Kasuwa, and Jahun, all located within the inner-city traditional settlement, are the worst hit by the windstorm destructions with "very high" damage severity (See Figure 8c). A in victim in Karofi described how the windstorm wreaked havoc on his property, with parts of his walls and rooftop falling victim to the powerful gusts. The rubble from the damaged walls fell onto his car, shattering its windshield and denting the bonnet. Another victim recounted how the windstorm's domino effect from flying debris unfolded. As the roofing materials from a nearby blown-off roof hit their building, the impact cascaded, leading to severe damage on their roof and walls. This ripple eefect exemplifies the devastating consequences of the 2018 windstorm events, where damage in one area can trigger a domino effect, resulting in widespread destruction.

Additionally, other areas outside the traditional settlements but with "very high" damage severity are Kandahar, and some

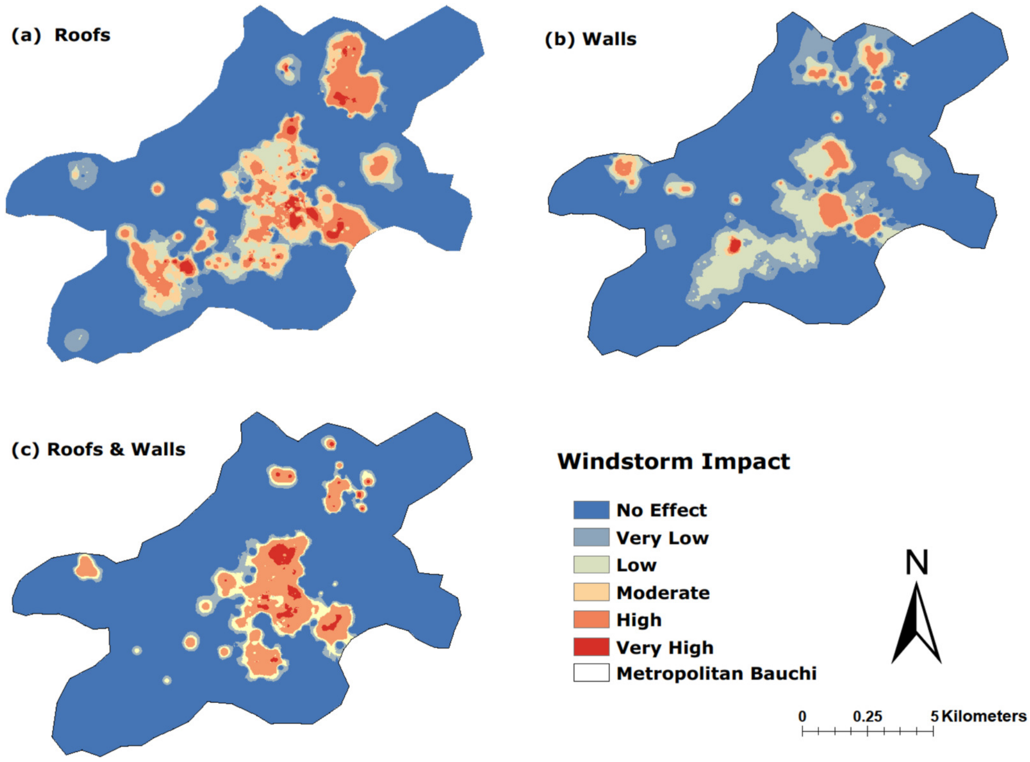

FIGURE 8
Windstorm hotspot maps showing degree of damage pattern based on EF-scale rating **(a)** damage to roofs, **(b)** damage to walls, and **(c)** damage to both roofs and walls.

parts of Zango and Turum. These neighborhoods are particularly vulnerable to severe windstorm damage due to factors such as densely compact housing, low-quality buildings, and inadequate resilient infrastructure. The findings suggest widespread devastation across various neighborhoods, with more than 50% of the affected area located within the inner-city traditional settlement. Other areas such as Zango, Kandahar, Bayan Gari, Magaji Quarters, and Turum also experienced similar levels of impact (See Figure 8c).

3.3 WCEE severity impact

The results of the fuzzy-AHP analysis reveal the hotspot pattern of WCEE impact across the study area. Findings indicate that 25% of the area has experienced varying degrees of WCEE impact during the study period. While the overall impact ranges between low and very low severity, certain areas, particularly within the inner-city traditional settlements, have been severely affected. These areas include Bakaro, Karofi, Shagari, Zannuwa, and Ungwan Mahaukata, among others, all ranked as "highly impacted." Additionally, other areas with similar rankings but outside the traditional settlement are Kandahar, Wuntin Dada, Turum, and Magaji Quarters (See Figure 9).

The study discovered that the worst-hit neighborhood by both flood and windstorm events, with a "very high" impact severity ranking according to the fuzzy-AHP assessment, is Korama (See Figure 9). This heightened impact can be attributed to several factors. Korama serves as a collection point for runoff water from adjacent neighborhoods such as New and Old GRA, and Yuguda Guesthouse. However, due to the lack of sufficient drainage channels, the accumulated water inundates the area, causing widespread damage to buildings. Additionally, Korama's status as a newly developed area, with significant portions of land converted to residential use from fadama, contributes to its vulnerability to flooding. The limited presence of trees in the area further exacerbates the situation, as they are unable to serve as effective windbreakers.

Furthermore, ongoing construction activities in Korama increase its susceptibility to windstorm damage. During the 2018 windstorm event, many buildings under construction suffered varying degrees of destruction. These findings underscore the urgent need for improved infrastructure and planning measures to mitigate the impact of WCEE on vulnerable communities like Korama."

4 Discussion

The analysis of flood impact unveiled a distinct pattern, particularly noticeable in specific neighborhoods. These areas are often in a state of panic due to consistent severe flooding, often with depths exceeding one (1) meter. The study discovered that flooding is a frequent occurrence in many of the affected areas, with incidents averaging seven times per year, and some locations experiencing seven and above occurrences annually. This recurring threat leaves residents in constant fear during the rainy season.

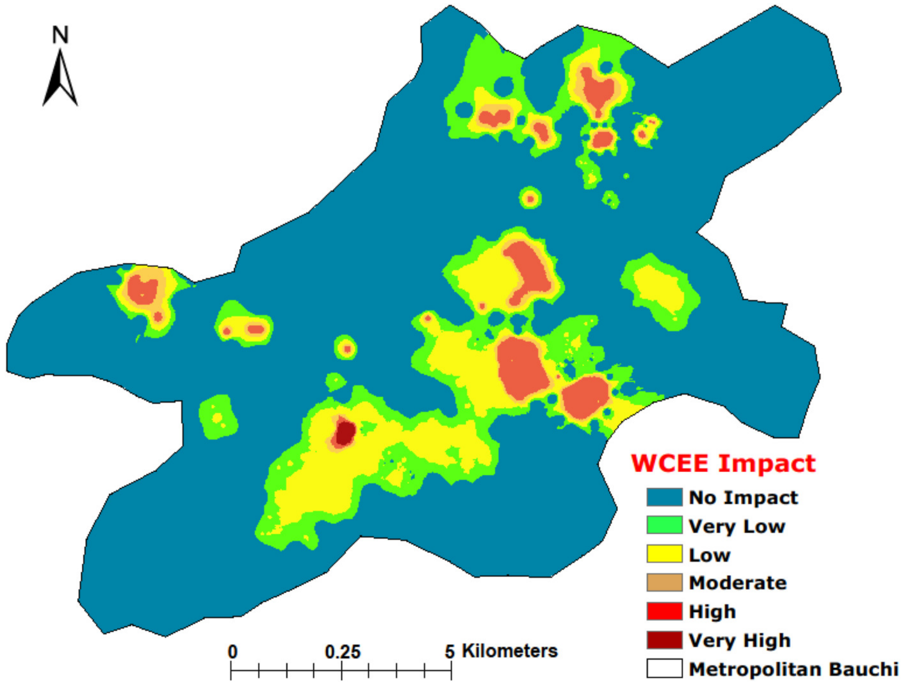

FIGURE 9
Hotspot map showing WCEE exposure and severity impact based on fuzzy-AHP criteria ranking.

Regarding the extent and depth of flooding, the study found that floodwaters typically spread less than 50 m in width and reach only a few centimeters in depth in most of the exposed neighborhoods. However, some areas experience flood levels exceeding 1 m, with residents reporting distressing experiences of water seeping into their homes through walls, doors, windows, and drainage outlets, rather than being properly directed away. These areas suffer the most severe impacts, including significant property loss and damage (Bouwer, 2019; Dilley and Grasso, 2016).

The consequences of flooding are extensive and deeply disruptive to affected communities. Structural deterioration is a common outcome, often manifesting in the form of crumbling plaster, cracked or collapsed walls, and damaged flooring, which collectively compromise the integrity of buildings. In addition to structural damage, flooding leads to the widespread destruction of household belongings, including furniture, carpets, electronics, and mattresses, significantly increasing the financial burden and impoverishing the affected residents. Essential property such as food supplies and livestock, which are critical for household sustenance and livelihood, are also frequently contaminated or lost (Reed et al., 2022; Shrestha, 2019). The psychological toll of this loss and damage is compounded in severe cases, where residents are not only displaced temporarily but also forced to evacuate permanently, abandoning their homes and communities in search of safer living conditions. This displacement often results in long-term social, economic, and emotional hardships, further highlighting the devastating impact of recurrent flooding. Neighborhoods like Bayan Kotu, Magaji Quarters, Fadaman Mada, Korama, and Madina Quarters are the classical case of areas with frequent flood-related impact, displacement, and occasional fatalities. These are neighborhoods with concentrations of residential buildings along waterways, fadama and waterlogged areas, and low elevations. The severity of flooding in these neighborhoods can be attributed to the prevalence of buildings on or encroaching upon waterways. Such encroachment significantly exacerbates the risk of frequent inundation, resulting in more extensive damage to properties and infrastructure during flood events. This amplifies the absence of effective development control measures and zoning regulations to check developments and ensure proper land use planning. Other contributing factors to the heightened flood incidences include inadequate drainage infrastructure and zoning regulations.

On the contrary, the windstorm impact analysis revealed a pattern characterized by the prevalence of destruction in densely populated areas, particularly within the compact and low-quality residential densities. Neighborhoods such as Bakaro, Karofi, and Jahun in the inner city and the suburban areas of Turum, Kandahar, and Zango experienced widespread destruction due to their structural vulnerabilities in addition to the domino effect of fleeing debris damaging neighboring structures and buildings due to their compact nature. Furthermore, the lack of resilient infrastructure, such as trees and sturdy buildings, further exacerbates the vulnerability of these communities to windstorm damage. Based on observed wind speed ratings, more than half of the recorded destruction occurs at wind speeds of approximately 67 ± 20 m/s, with damage typically unfolding in less than 2 hours following the onset of the extreme event (Kafi et al., 2021). These high-intensity winds are particularly alarming, as they have only been experienced in recent years. Many older residents, familiar with the historical weather and climate patterns of Bauchi, have acknowledged that such destructive winds—capable of uprooting baobab, neem, and other indigenous trees, toppling electric poles and telecommunication masts, and severely damaging buildings, including blowing off the roofs of hundreds of structures and causing loss of life—were unknown in Bauchi over the past 30 years. The increasing frequency and intensity of these extreme wind events are closely linked to the broader impacts of climate change, exacerbated by human activities. Approximately 45% of buildings in metropolitan Bauchi do not meet construction codes, making them highly vulnerable to structural failure. Additionally, the absence of resilient infrastructure—such as sturdy buildings and tree abundance—further compounds the devastating loss and damage impacts of windstorms. These findings align with previous studies that emphasize the vulnerability of the built environment to extreme events driven by climate change (Birkmann et al., 2022; Chike, 2017).

The first study's research question aimed to identify the areas most impacted by flood and windstorm and their triggering factors. Using the fuzzy-AHP MCDA approach, the findings show that five neighborhoods are severely and disproportionately affected by floods due to their location along waterways, fadama zones, and low-lying elevations, while six neighborhoods within the inner-city areas such as Bakaro, Karofi, and Jahun, and suburban communities like Turum, Kandahar, and Zango, are most affected by windstorms. Their vulnerability stems from poorly constructed or aging buildings, compact urban layouts that intensify debris damage, lack of natural windbreaks, and weak infrastructure. These results pinpoint the worst-hit areas and explain the environmental, structural, and spatial triggers, thus directly addressing this research question.

The overall loss and damage impact caused by flooding and windstorms provide a clear visualization of the spatial distribution and severity of WCEE across the study area. With 25% of the total area affected by varying degrees of loss and damage, the study provides an understanding into the disproportionate nature and patterns of WCEE impacts in Bauchi over the study period. Similarly, the findings underscore the critical need to build and transform Bauchi into a more resilient urban environment (Rus et al., 2018). Therefore, policymakers and urban planners should prioritize initiatives aimed at upgrading the neighborhoods, especially those severely affected by recurring floods and windstorm disasters. Although there have been recent conscious efforts by the Bauchi State Government towards urban renewal within the traditional settlement of Bauchi through the construction of resilient infrastructure such as road and drainage networks, similar projects should be replicated in suburban areas exhibiting similar settlement patterns and building quality. Furthermore, there is the need to integrate the practical realities of present and past disaster and hazard areas into comprehensive spatial planning initiatives, which is crucial for ensuring safe and sustainable future planning (Kodag et al., 2022). This includes implementing effective development control measures to regulate the construction of non-code-compliant buildings and construction activities in flood-prone areas to enhance disaster risk reduction.

5 Conclusion

In conclusion, the findings of this study highlight the pattern and multidimensional impacts of WCEE across Bauchi city, particularly concerning flood and windstorm hazards. Through the utilization of decision-making analytical techniques such as fuzzy-AHP and IDW spatial interpolation technique, the study has provided valuable insights into the spatial distribution of various WCEE impacts in Bauchi. By assigning weights to each impact indicator based on fuzzy-AHP criteria and overlay analysis, the study reveals areas with an overall high exposure impact to the twin disasters. The findings reveal disproportionate impact of flood and windstorm disasters across different neighborhoods, with some areas experiencing more severe effects. Specifically, neighborhoods with physical and social vulnerabilities like insufficient drainage infrastructure or residential buildings encroaching on water channels suffer the most from flooding. In contrast, organic settlement characterized by compact housing, high population density, and non-compliant buildings, particularly in the traditional city and suburban zones, are more severely affected by windstorms. This valuable finding emphasizes the urgent need for proactive and targeted measures to enhance disaster risk reduction and resilience in the region.

Moving forward, policymakers and urban planners must integrate these findings into comprehensive disaster management strategies and spatial planning initiatives. This involves implementing effective development control measures, establishing resilient infrastructure like drainage systems, tree conservation and planting exercises, and adopting zoning regulations to enhance disaster risk reduction. By prioritizing resilience-building efforts and incorporating hazard mitigation measures into future planning processes, Bauchi city can strengthen its capacity to withstand and recover from WCEE events, ensuring the safety and wellbeing of its residents in the face of increasing climate-related risks. Furthermore, through conscious effort, policymakers and urban planners can prioritize the most impacted areas for intervention and implement targeted mitigation measures to enhance resilience and reduce the adverse effects of WCEE on communities and infrastructure.

Based on our study findings, which reveal how Bauchi is disproportionately impacted by severe flood and windstorm disasters, further study is crucial to understand the effectiveness of disaster risk reduction (DRR) policy and practices in Bauchi city.

Lastly, this study recorded only location coordinates and associated damage and exposure information. As data on victims' socioeconomic indicators were not collected, the analysis could not explicitly assess how vulnerability varies across income or demographic groups, limiting the identification of the most socially vulnerable populations. Therefore, future studies should integrate socioeconomic data to better understand differential impacts and support more targeted risk reduction and adaptation strategies.

Data availability statement

The data presented in this article is not readily available because of its sensitive nature and the fact that this is an independent study. The authors agree that data for the study will be available on reasonable request.

Ethics statement

Ethical approval was obtained from the University Ethical Committee (JKEUPM) with approval number JKEUPM-2023-1150 prior to the commencement of the data collection exercise. The studies were conducted in accordance with the local legislation and institutional requirements. The participants provided their written informed consent to participate in this study. Written informed consent was obtained from the individual(s) for the publication of any potentially identifiable images or data included in this article.

Author contributions

KK: Conceptualization, Data curation, Formal Analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Validation, Visualization, Writing – original draft, Writing – review and editing.

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Generative AI statement

The author(s) declared that generative AI was used in the creation of this manuscript. Generative AI was used in grammar improvement.

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