Flood Susceptibility Mapping of Internally Displaced Persons Camps in Maiduguri, Borno State Nigeria

Taiwo Ogunwumi (taiwoogunwumi@yahoo.com)
United Nations University, Institute for Environment and Human Security (UNU-EHS),
Chukwudi Njoku
3Department of Geography and Environmental Science, University of Calabar, Calabar, Nigeria
Arinze Uzoezie
Department of Geography and Environmental Resource Management, University of Calabar, Calabar, Nigeria.
Iniobong Benson
Department of Geoinformatics and Surveying, University of Uyo, Ikpa Road, Uyo, Akwa Ibom Nigeria

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Abstract

Increasing climate variability is causing an increase in flood occurrence, affecting vulnerable individuals who have been displaced by the insurgency and conflicts that occurred in the past years. The decade-long insurgency in northeast Nigeria is one of the most pressing humanitarian crises on the continent, with over 2 million people displaced from their homes by conflict and political instability. These yearly floods destroy campsites occupied by displaced families who fled from conflict zones.

This study applied the multi-criteria approach, Geographical Information System, and Remote Sensing. Analytical processes such as buffering, slope generation, interpolation, reclassification, and the weighted overlay were performed through the GIS environment to generate a flood susceptibility map indicating four zones (very high, high, low and very low-risk). A total number of **25 of 35 Internal displaced campsites** are within the high susceptibility while **4 camps are prone to a Very high flood risk level (SULUMBURI DOGON ICHE, GRA, SULUMBURI CAMP, and FULATARI FARIN RUWA). Based on our results**, camps located close to water bodies will be submerged by flood during the coming raining seasons if actions are not taken in time.

This paper is a vital for appropriate government agencies such as town planners, emergency management agencies, international NGOs, the United Nations Office for the Coordination of Humanitarian Affairs, and other important stakeholders who can implement preparedness, evacuation planning, and early warning to the populace and Internally displaced individual at various campsite and settlement within the inferred flood risk zones.

1.0 Introduction

Flooding is a disaster caused by multiple related factors such as hydro-meteorological, anthropogenic, and geomorphological factors (Emberga, 2014). It is the most frequent type of natural hazard that occurs when there is an excessive flow of water that submerges land (World Health Organization- WHO, 2021). Recent flood occurrences and consequences all over the world are becoming too frequent and threaten the sustainability of human settlements (Aderogba, 2012). Floods can cause widespread devastation, resulting in the destruction of property, public health infrastructure, and loss of life. For instance, between 1998–2017, floods affected more than 2 billion people worldwide (WHO, 2021). In 2020 alone, flood occurrence affected more than 2.7 million people in 18 countries in West and Central Africa and many regions recorded excess rainfalls (United Nations Office for the Coordination of Humanitarian Affairs- UNOCHA, 2020).

Nigeria can be considered as one of the fortunate countries on earth in terms of natural hazard occurrence compare to other countries of the world. However, the country is familiar with the devastation of flooding (Magami, Yahaya, & Mohammed, 2014). Flooding is the most frequent disaster in Nigeria (Echendu, 2020). The south-western region of the country, the Niger Delta, and communities situated downstream of rivers in the northern region are constantly affected by flooding. In 2012, Nigeria experienced its worst flooding event in recent history (UNOCHA, 2012; Nkeki, et al, 2013; Toure, 2014). The disaster resulted in the displacement of more than 2.3 million people, with a casualty of 363 persons and other impacts on over 16 million people (Echendu, 2020). Total losses summed up to US$16.9 billion (Security, 2013).

Flooding is commonly thought of as a manifestation of heavy and continuous rainfall. However, floods can manifest as a result of natural and anthropogenic factors. The common factors are excessive rain, overflow of river banks, and rapid ice melting in the mountains (National Geographic, 2018). In Nigeria, although climate change has led to an increasing rate of rainfall occurrence recently than in the past, which consequently has led to an increase in flooding, flood occurrence is mostly human-induced and aggravated by the interaction between man and nature (Aderogba 2012). Some examples of the unfavourable man and nature interactions that exacerbate the occurrence of flooding in Nigeria are poor waste management system, unregulated urbanization, bad or non-existent drainage systems and weak implementation of landscape planning regulation, and bad governance (Ogundele & Jegede 2011; Ojo & Adejugbagbe 2017).

Flooding events, regardless of meteorological and topographical factors, are becoming acute due to rapid urbanization (Suriya & Mudgal, 2012), environmental changes, such as land-use change, climate change (Detrembleur, et al., 2015), and poor planning (Ojo & Adejugbagbe, 2017). However, with efficient flood risk management (FRM), flood disasters can be effectively managed (Lumbroso, Ramsbottom & Spaliveiro, 2008). FRM avails an early warning system that aids in the preparation against flooding occurrence. People who live in areas that lack warning systems and awareness of flood hazards are most vulnerable to flooding.

In Nigeria, susceptibility to flood is evident and imminent. This susceptibility is not limited to settlements around coastal regions with high and frequent rainfall occurrences such as Lagos, Kogi, Cross River, and Anambra. Deserts and desert-like areas with low rainfall frequencies as well experience floods from heavy, though infrequent downpours (Nicholls, 1987). While the occurrence of flooding in Borno State is a fact, such disaster in a dry belt is regarded as almost a myth (Odihi, 1996). This “hydroclimatic fallacy” according to Odihi (1994) is influenced by the absence of flood mitigation measures and preparedness planning in the State.

Borno State, and specifically, its capital, Maiduguri is of particular interest to this study because of the susceptibility of internally displaced persons (IDP) settlements to flood risk. These IDP settlements situated in the north-east of the country are made up of victims of the decade-long Boko-Haram insurgency. For instance, on July 6, 2012, torrential rains in Maiduguri caused the displacement of many residents from their various homes, destroyed IDP camps and properties worth millions. This particular flooding event caused damages to the Jajeri Muslim Cemetery (Shettima, 2018). According to the situation report released by UNOCHA (2019), an estimated 10,490 emergency and makeshift shelters in various IDP camps were damaged due to the flooding, while some other host communities were inundated. Also, in August 2020, another heavy rain destroyed makeshift tents at various displacement camps in Borno and Yobe states Nigeria, thereby leaving vulnerable families homeless. According to Norwegian Refugee Council's (NRC) assessment which was conducted after the flood event, over 6,800 people living in displacement camps in Maiduguri were impacted. As a result, such a large number of individuals, who escaped from the conflict which occurred a decade ago, are now rendered homeless again (NRC,2020).

The increase in flood events coupled with low coping capacity and high vulnerability of the IDP's have continued to put many lives and properties at risk (UNOCHA, 2019; NRC, 2020; Komolafe, Adegoyega & Akinluyi, 2015). In previous years, there have been various interventions to mitigate the incidence of flooding, but many of these interventions lack the integration of sustainable FRM systems and practices in Nigeria (Adedeji, Odufuwa, & Adebayo, 2012). A Sustainable FRM system reflects the ecological make-up of infrastructural development, institutional behavior and other techno-socio-economic characteristics of an environment (Oladokun & Proverbs, 2016). Flood risk management is aimed at minimizing the likelihood and/or the impact of floods and it is an integral part of integrated river basin management (European Commission, 2020). The absence of detailed flood risk maps, for instance, contributes to the lack of attention being paid to flooding preparedness and mitigation in Nigeria (Oladokun & Proverbs 2016). This suggests the need for the design and implementation of adequate FRM strategies, which would comprise of proper spatial planning, flood susceptibility mapping, and setting up the necessary infrastructure for controlling flood occurrences (Ouikotan, et al., 2017). Sustainable FRM can be achieved through the provision of a flood risk model or maps that show the spatial distribution of flood risk levels at different zone of a particular area.

Flood risk mapping in Maiduguri has been done by a few authors. The recent works on flooding in Maiduguri were carried out by Jimme, Bashir, and Adebayo (2016), who examined the spatial pattern of urban flash floods and inundations, as well as the terrain characteristics in Maiduguri metropolis. The researchers adopted the Multiple Criteria Analysis (MCA), using parameters such as elevation, flow accumulation, and slope to map out potential flood risk areas. Similarly, Shettima, 2019 and Mayomi, 2014 adopted the MCA to assess the vulnerability of flooding in Maiduguri, using topography delineation.

The Multi-Criteria Analysis or MCA is a GIS technique adopted in selecting suitable sites or mapping vulnerability. The techniques are used to consider several criteria in order to make decisions (Ryan &Nimickm 2019). The MCA is adopted when there are there many independent factors considered in evaluating a phenomenon. MCA can be adopted in environmental problems where there may be multiple favourable solutions. For instance, in flood vulnerability evaluation where there are several causes such as hydro-meteorological, anthropogenic, and geomorphological causes, the MCA becomes a suitable technique in evaluating flooding vulnerability.

The selection of effective parameters is essential and some important variables have a definitive role in the creation of flood susceptibility mapping (Samanta, Koloa, Pal & Palsamanta, 2016). Notwithstanding this, there is limited research in Maiduguri that has considered the integration of rainfall, topography, proximity to river, and land use parameters in the analysis flood susceptibility around vulnerable settlements like IDP camps. Although there are reports on the impact of flooding on IDP camps, there is a dearth of research focused on mapping the susceptibility of the settlements, hence, an apparent lack of flood susceptibility maps that facilitate sustainable FRM in IDP camps.

This motivated the need for this study to efficiently identify the susceptibility of IDP camps to flooding by adopting the GIS Multi-Criteria Approach (MCA), most specifically the analytical hierarchical process (AHP) which involves the combination of multiple datasets such as rainfall, slope, elevation, land use type and distance to the water bodies like in previous studies (Owusu, et al., 2017; Komolafe et al, 2020, Cabrera, 2020, Njoku, *et al.*, 2020; Ogunwumi et al., 2021 and Ozturk et al., 2021). This study thus specifically mapped flood-risk susceptibility in Maiduguri, determined the area coverage of each flood-risk zone, mapped the number of IDP camps and the population of Internally Displaced Persons within each zone.

1.1 Study Area

Maiduguri is located between latitudes 11° 42'N and 12° 00' N and longitudes 12°.54' and 13° 14' E with an area coverage of 131 km^2 (Haruna, 2010). It is the capital and the largest city of Borno State in northeastern Nigeria. The city sits along the seasonal Ngadda River, which disappears into the Firki swamps in the areas around Lake Chad. The city is bounded in the north by Jere LGA, in the west, south and south-west by Konduga LGA, in the north-west by Mafa LGA (Fig. 1).

Maiduguri has a mean annual maximum temperature of 34.8, and receives an average rainfall of 552.1mm (21.74") from June to September (Mayoni, 2014). Maiduguri is generally drained by seasonally flowing rivers, whose peak flows are recorded during the rainy season in the month of July and August. Maiduguri is drained mainly by River Ngadda with Ngaddabul as its major tributary. The vegetation of Maiduguri is similar to the Sahel Savannah surrounded by shrubby vegetation interspersed with tall tree woodland, annual grasses form the vegetation cover of Maiduguri, especially during the rainy season (Shetima 2018).

According to National Population Commission (NPC), the estimated population of the city in the year 2008 was 1.275 million people with an annual growth rate of about 3.5% and a density of 1145 persons per square km which makes it the most densely populated city in north eastern Nigeria. The projected population of Maiduguri Metropolis for the year 2011 stood at 2,722,986. (NPC, 2008).

2.0 Materials And Methods

2.1. Data types and sources

The types of data used for this study include rainfall data, elevation, satellite imagery, administrative boundary data as well as the number of IDP campsites and population size of the Internally Displaced Persons. The Advancing Land Observing Satellite (ALOS) - Global Digital Surface Model was acquired for the map of Elevation. The list of IDP campsites and population size of each site were sourced from the Displacement Tracking Matrix Round 33- United Nations Migrations. Also, for this research, annual rainfall data was acquired from Nigeria Meteorological Agency (NIMET) rainfall prediction for the year 2020. The other multiple datasets considered in this research are listed in the table below.

Table 1
Data information

Data type	Source	Year	Mapping Output
Elevation (Digital Elevation Model-DEM)	Advancing Land Observing Satellite -ALOS Global Digital Surface Model data (30x30m^2 resolution)	2020	Elevation, slope, distance from minor rivers.
Satellite imagery (Sentinel 2)	http://scihub.copernicus.eu 10 –meter resolution obtained from the Open Access Corpenicus Hub.	2021	Land use map
Water-body shapefile	Digitized from Google Earth Pro	2021	Distance from major river
Administrative LGA boundary shapefile	Borno State Geographic Information Service (BOGIS).	2020	Study area map
Rainfall	NIMET Seasonal Rainfall Prediction (SRP) acquired from the NIMET	2020	Precipitation/ rainfall map
IDP campsite and population size	Displacement Tracking Matrix Round 33- United Nations Migrations. https://displacement.iom.int/nigeria	2020	Spatial mapping of IDP campsites

2.2 Parameters inputs for MCA

2.2.1 Digital elevation model

The DEM is a fundamental criterion for flood susceptibility mapping. Surface runoff usually flows from areas of high elevation and accumulates at areas of low elevation height. Therefore, due to gravity influence, areas of lower altitudes are highly susceptible to flood occurrence (Das, 2019). The DEM map (Fig. 2) shows that the elevation of Maiduguri ranges from 321 meters to 355 meters above sea level, indicating that the northern parts of Maiduguri have low elevations while the south-western parts of the city are of very high elevation.

2.2.2 Slope

The slope is a product that can be extracted from the DEM and an important parameter for accessing flood susceptibility. The slope of a given location determines the quantity and direction of surface runoff entering the area. Thus, the areas with very low slopes are more susceptible to flood due to water accumulation while locations with a high slope (gentle terrain) are less can slow down the occurrence of flooding (Cabrera, *et al*., 2020). The slope angle of Maiduguri ranges between 1.5° and 16.0°. **(**Fig. 3**)**

2.2.3 Rainfall Intensity

The intensity of rainfall is a measure of the amount of rain that falls over time (Floodsite, 2008). The intensity of rain is measured in the height of the water layer covering the ground in a period of time. Geographical variation in the intensity, duration, and amount of rainfall at a given location is one of the determinants of flooding (Mirzaei et al. 2020). When there is a higher intensity of rainfall, there is an increase in the amount of surface runoff and a higher discharge from the major rivers. To produce a precipitation map for this study, the annual rainfall intensity data was acquired from the NIMET and interpolated. As shown in Fig. 4, the northern parts of the study area have a much lower rainfall intensity in contrast to the southern parts, putting the former at a higher chance of experiencing flooding.

2.2.4 Land Use

Land use/ land cover (LULC) type is another essential factor that contributes to the occurrence of flooding. Areas concentrated by buildings and road networks are highly susceptible to the impacts of flooding, due to drainage blockage and the impermeable surfaces such as tarred roads. The area that is cover by river or water bodies is also highly susceptible to flooding due to river overflow (Welde & Gebremariam, 2017). In contrast to built-up and river land use type, vegetation (area covered by dense or light forest) zones contribute less to the occurrence of flooding simply because the zone has a higher amount of infiltration that acts as water storage leading to a reduction in the amount of run-off.

The LULC classification map (Fig. 5) of the study area was derived using Sentinel 2A data (January 28, 2021) at a 10m resolution. Color composite of the study area was done by aggregating the Bands 8, 4, and 3 of the Sentinel 2 imageries for the classification. Training sites were selected according to the spectral signature of each cell and the maximum-likelihood-based supervised classification and other preprocessing and post-processing techniques were applied to generate the landuse map of the study area. In this study, three different classes were defined: built-up/ bare land, vegetation, and river.

2.2.5 Distance from big and small rivers

Distance of settlements to the nearest riverbanks is a determinant of flood susceptibility, the level of flood risk is low for settlements or locations farther to the rivers or streams. Thus, emphasizes the essence of analyzing the distance from river in flood risk research (Kazakis, et al., 2015). To understand the distance variation to the nearest river, the buffer-processing tool in ArcGIS was used to generate a multi-buffer of 1000 meters (Fig. 6) for the major rivers while a 500 meters progressive interval was used to determine the distance from the small or minor rivers. The choice of buffer distances used for this study was based on the previous findings of Pourghasemi (2009) and Rahmati, et al. (2016). According to Ghosh, *et al*. (2018) and Bui, et al. (2019), large water bodies with enormous volumes contribute to the occurrence of flooding most especially when they overflow their banks.

3.0 Reclassification And Rating Process

Reclassification of the dataset is a prerequisite for weight assignment (Komolafe, et al., 2020) simply because all the flood parameter datasets are of varying units and measurement scales. Therefore, to weigh the cumulative scores of all the parameters, it is necessary to group each to the same scale with other parameters. In this study, each parameter is reclassed to four using the natural break methods as shown in (Table 5). The class interval with the highest influence in flood initiation was assigned a value of 1, while the class interval with the least flood hazard induction was assigned 4 (Njoku, *et al.*, 2020). The reclassified distance to the river was given a value 1 for the distance of < 500m and < 1000m for both small and big rivers respectively, while the other distances from the rivers were assigned 2 to 4 accordingly (Fig. 8, 9). The elevation and slope were reclassed based on height and degree; that is, the lower values of elevation and lower percentages for slope were assigned 1, while the others were assigned between 2 to 4 (Figs. 10 and 11). The LULC classes of the study area were reclassed by their capacity to increase or decrease the rate of flooding. Waterbody and built-up areas which are more prone to flooding were reclassed as 1 and 2 respectively, while vegetation was assigned the value of 3 as shown in (Table 6). The result of the reclassed maps is shown in Figs. 8, 9, 10, 11 and 12.

The rating is user-defined (Table 6) and is supported by previous literature (Samanta et al., 2016a, Komolafe, et al., 2020). The ranks were further grouped into a rating index of very high, high, low and very low-risk groups.

3.1 Analytical Hierarchical Approach

The AHP was developed by Saaty (1980, 1990) and is a decision-making approach and a comprehensive technique for solving complex issues using pairwise comparisons of multiple variables and expert judgments to obtain priority scales for further weight analysis using the GIS environment. There are several weight estimation techniques, but the AHP is considered a powerful technique in the field of hazard mapping as it produces rapid, cost-effective and the most reliable performance (Pourghasemi, et al., 2012). The model is categorised into four different step-by-step stages which includes "assigning of weight, computing of pairwise comparison matrix, normalization of weight and consistent checks".

In this study, the AHP model was adopted in assigning weights to each of the six parameters which served as the flood susceptibility indicators. To compare all the indicators/ parameters against each other in a matrix format, the weight of each parameter was assigned using the Satty scale (Table 2). Based on this preference scale, all factors were compared in pairs in the range of 1–9. How important a factor is in comparison to the other was decided based on the literature survey and the numerical value expressing this degree of importance was determined using Table 2 which was used to compute the pairwise comparison table (Table 3). To determine the relative weight of the parameters which sum up to a total weight of 1 otherwise known as the normalized pairwise table (Table 4), the columns in the pairwise comparison table are summed and each cell value is divided by the column sum. The weight was derived by obtaining the mean of the normalized matrix values for each row (Table 4).

3.1.1 Consistency measurement

Consistency Ratio

The calculation of the consistency ratio of the computed pairwise comparison is used to judge the accuracy and excellence of the final output derived from the AHP Model. Hence, the result of the consistency ratio serves as a check to know whether the AHP process is reasonably consistent or not, if not consistent, then there will be a need to repeat the pairwise computation. The consistent ratio can be derived by dividing the Consistency Index (CI) by the Random Index (RI).

Consistency Index

The Consistency Index (CI) is used to measure the degree of inconsistency in the square matrix (Piantanakulchai, t & Saengkhao, 2003). To determine the consistency index, we used the formula stated below:

$(\lambda max - n)/(n-1)$ Eq. (1)

λmax = is the principle Eigenvalue

n = represents the total number of parameters used for this study.

In this study, the calculation of **λmax** is equal to **6.323553** while n is equal to **6.** Using the consistent index formula (Eq. 1) the final value is equal to **0.064711**

Random Index

Random Index is the average of C.I values of various sizes of comparison matrices (Shyamprasad & Kousalya, 2020). The evaluation of R.I values for higher-order comparison matrices can be complicated. In this study, since we used six parameters to compute the pairwise comparison, to determine the random index, we used the Random Index (Table 5) column and choose the named column 6 which equals **1. 24.**

Consistency Ratio = CI/RI

Consistency Index = 0.064711 / Random Index = 1.24

Consistency Ratio = 0.051769

The consistency ratio result was 0.051, which is smaller than the 0.10 limit value suggested by Saaty (1980), so the pairwise comparison judgments are consistent and it proves the acceptability of the procedure in analyzing the impact of each parameter to determine the final flood susceptibility.

3.2 Weighting Process

To determine the final weighting for each parameter, the percentage of the weights derived from the AHP was calculated (Table 5). The weighted overlay analysis tool in the ArcGIS Pro was used to compute all the weight percentages for each of the six parameters (distance from big river – 35.8%, rainfall – 24.8%, elevation – 17.4%, slope – 13.8%, landuse – 5% and distance from small river – 3.1%) as shown in Table 5. This aided to produce the final flood-risk susceptibility map grouped into 4 zones from the very high risk to the high risk, low risk and very low-risk zones (Fig. 12).

Table 2
Analytical Hierarchical Process (Preference scale)

Rating of Importance	Definition
1	Equal importance
3	Moderate importance
5	Strong importance
7	Very strong importance
9	Extreme importance
2,4,6,8	The same importance

Source: Saaty, 1980

Table 3
Pairwise comparison Matrix

Parameter	Distance from big rivers. *(DBR)	Distance from small river (DSR)	Rainfall	Elevation	Slope	LandUse
DSR	1	1/7	1/7	1/5	1/5	1/3
DBR	7	1	2	3	3	5
Rainfall	7	1/2	1	2	2	5
Elevation	5	1/3	1/2	1	2	5
Slope	5	1/3	1/2	1/2	1	5
Landuse	3	1/5	1/5	1/5	1/5	1

Table 4
Normalised pairwise comparison and weight value for each of the six parameters

Parameter	DSR	DBR	Rainfall	Elevation	Slope	LandUse	Geometric Mean	Weight
DSR	0.036	0.057	0.033	0.029	0.024	0.016	0.255	0.031
DBR	0.250	0.398	0.461	0.435	0.357	0.234	2.928	0.358
Rainfall	0.250	0.199	0.230	0.290	0.238	0.234	2.030	0.248
Elevation	0.179	0.133	0.115	0.145	0.238	0.234	1.424	0.174
Slope	0.179	0.133	0.115	0.072	0.119	0.234	1.130	0.138
Landuse	0.107	0.080	0.046	0.029	0.024	0.047	0.411	0.050
Total							**8.177266**	**1.00**

Table 5
Random Index

n	1	2	3	4	5	6	7	8	9
RI Value	0.00	0.00	0.58	0.90	1.12	**1.24**	1.32	1.41	1.45
Source: Saaty, 1980									

Table 6
Multi-criteria data reclassification and rating

Parameters	Classes	Reclass (rating)	Rating index
Distance from rivers (m) (big and small)	< 500, < 1000	1	Very high risk
	2000	2	High risk
	5000	3	Low risk
	10000	4	Very low risk
Elevation (m)	< 321	1	Very high risk
	< 328	2	High risk
	< 334	3	Low risk
	< 355	4	Very low risk
Slope	1.5	1	Very high risk
	< 2.8	2	High risk
	< 4.7	3	Low risk
	< 16.0	4	Very low risk
Land use	Waterbody	1	Very high risk
	Built-up	2	High risk
	Vegetations	3	Low risk
Rainfall	520mm	4	Very low risk
	< 525mm	3	Low risk
	< 530mm	2	High risk
	< 533mm	1	High risk

Table 7
Final weights for all the parameters based on the pairwise result

Parameter	Weight	Weight (%)
DSR	0.031	3.1
DBR	0.358	35.8
Rainfall	0.248	24.8
Elevation	0.174	17.4
Slope	0.138	13.8
Landuse	0.050	5.0
Total		**100%**

Reclassified maps of the study area.

[See figures 9-14.]

4.0 Results And Discussions

The MCA revealed the different levels and extent of flood-risk susceptibility in Maiduguri. As deduced and shown in Table 3, 1.3 percent of Maiduguri's total area coverage face very low flood-risk and 48.9 percent face low risk. A total of 43.7 percent of the city's coverage is in high flood-risk zone and these are mostly areas in the south of the city (Fig. 15). Similarly, 6 percent of the city settlements close to rivers might be faced with very high flood-risk susceptibility. The deduction from this study is that 49.7 percent of the city is in high to very high flood risk zones and this corroborates with the finding of Bwala, Oladosu, and Nghalami (2015) that about 62% of Maiduguri inhabitants had hitherto experienced flooding, yet are still occupying the flood-risk areas. This risk exposure was attributed to the family origin, cheapness of land and low cost of house rent, poor finance, unavailability of space and of course, the emergence of Internally Displaced Persons.

The very high and high-risk zones are locations where flooding can emanate without bustle as a result of seasonal and also periodic rainfall that can over saturate the soil and also make the rivers overflow their banks. On the other hand, the very low and low-risk zones are locations where the chances of flooding might be minimal but can still be triggered by extreme natural events.

Further analyses revealed that out of the 35 IDP campsites identified in the city, 11.4 percent are in the very high flood risk zone, 60 percent in high risk, and 11.4 percent in low flood risk zone (see Table 9 **and** Fig. 16). Likewise, as shown in Table 9, **52**.6 percent of the Internally Displaced Persons will face high flood risk and 20.7 percent of the displaced population will be faced with very high risk of flooding. The scenario of previous flooding events in GRA and Stadium IDP campsites is pictured in **Plate 1 and 2**.

Internally displaced persons are more vulnerable to flood disasters where they find themselves in such hazardous areas. Their vulnerability is exacerbated by absolute poverty and their lack of knowledge of disaster preparedness. Thus, the situation that 35,647 Internally Displaced Persons (73.3 percent) reside in high to very high flood risk zones in Maiduguri calls for concern. This scenario is similar to that of Khammam region in India where flooding impacts food security and livelihoods of IDP's (Ramakrishna, Gaddam and Daisy (2014). According to the BBC (2019), refugees are at an increased risk from extreme weather, with flooding being the major challenge that has led to the destruction of IDP camps in Maiduguri, Nigeria; Dafur, Sudan; Maban County, South Sudan, Cabo Delgado, and Mozambique.

Table 8
Area coverage of the different flood risk levels in the study area.

Risk level	Area (sqkm)	Percentage
Very low risk	1.7	1.3
Low risk	63.9	48.9
High risk	57.1	43.7
Very high-risk level	7.9	6
Total	130.6	100

Table 9
IDP campsites within the study area and their susceptibility level to flooding.

S/n	IDP campsite	Risk level	Population size
1	Fulatari farin ruwa	Very high risk	283
2	GRA	Very high risk	5463
3	Sulumburi camp	Very high risk	1985
4	Sulumburi Dogon Iche	Very high risk	2348
5	Biafra camp	High risk	320
6	Eyn Can Centre camp	High risk	144
7	Mogcolis camp	High risk	0
8	Stadium camp	High risk	864
9	Suleimanti	High risk	13343
10	Musune	High risk	118
11	Kuru camp	High risk	143
12	Kori camp	High risk	591
13	Umarari camp	High risk	219
14	Ali Goni	High risk	415
15	Ali Askira	High risk	223
16	Askira street	High risk	207
17	Jerusalem camp	High risk	984
18	Kulolori	High risk	5971
19	Modu Sulumburi	High risk	0
20	Fulatari	High risk	1425
21	Mashidimami camp	High risk	0
22	Babban Gida 1	High risk	0
23	Babban Gida 2	High risk	601
24	Yajuwa camp	High risk	0
25	Ajiri Yajuwa camp	High risk	0
26	Dubai	Low risk	2251
27	Garba Buzu	Low risk	781
28	Shagari Lowcost B/African Mission Global	Low risk	778
29	Umara Bolori camp	Low risk	0
30	Dogon Gida camp	Low risk	0
31	Beni Farin Gida	Low risk	0
32	Bayan Texaco	Low risk	2266
33	Nysc camp borno	Low risk	3337
34	Shuwari camp	Low risk	1645
35	Polo camp	Low risk	1872
	Total		**48577**

Table 10
Proportion of camps and their flood risk levels

Risk level	Number of IDP camp sites	Percent	Population	Percent
Very high risk	4	11.4	10079	20.7
High risk	21	60	25568	52.6
Low risk	10	28.6	12930	26.6
Total	**35**	**100**	**48577**	**100**

4.1 Conclusion and recommendations

In view of the findings from this study, as the rainy season approaches in Nigeria, floods are expected to affect many IDP camp sites situated in flood-vulnerable locations in Maiduguri. These floods would increase the stress on Internally Displaced Persons who are already vulnerable, while also presenting them with health risks such as malaria and cholera. This study adopted the use of GIS MCA to analyze flood-risk susceptibility and present outputs in an all-inclusive manner which will support better decision making.

The final output from this study is vital to the appropriate government agencies such as town planning departments, national/ state emergency management agencies, international NGOs, UNOCHA and other important stakeholders who are potential end-users of the research findings.

Using the forecasts about areas that are susceptible to flooding, onsite specific preparedness or evacuation planning and early warning information should be given to the populace and Internally Displaced Persons at various campsites and settlements within the inferred flood-risk zones. Damages and losses can be avoided if a timely warning is dispensed as it will allow inhabitants of a potentially floodable area to take actions that would save their lives and assets, and in effect reduce their vulnerability to future flood occurrence.

Furthermore, the flood-risk map derived herewith should be employed during the planning and design stage of the IDP camps, such that camps are not situated in locations that are susceptible to flooding. However, for camps that are already existing in flood risk zones, the construction of drainage channels capable of putting to check the floodwaters in areas that are of high and very high risk are necessary at all the IDP camp sites. Also, with the flood risk maps, relocation and evacuation would be timely for the residents in danger zones.

Declarations

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Conflict of Interest: The authors declare no conflict of interests.

Data Availability: The datasets generated and analyzed during the current study are available from the corresponding author on reasonable request.

References

1. Aderogba, K. A. (2012): Substantive Causes and Effects of Floods in South Western Nigeria and Sustainable Development of the Cities and Towns.Journal of Emerging Trends in Educational Research and Policy Studies 3(4): 551–560
2. Adedeji, O.H., Odufuwa, B.O. & Adebayo, O.H., Building capabilities for flood disas-ter and hazard preparedness and risk reduction in Nigeria: need for spatial planning and management. Journal of Sustainnable Development in Africa, 14(1), pp. 45–58, 2012.
3. BBC (2019). Refugees at 'increased risk' from extreme weather. Available via https://www.bb c.co m/news/scien ce-e nvironment-50692857
4. Bui DT, Khosravi K, Shahabi H, Daggupati P, Adamowski JF, Melesse AM, Thai Pham B, Pourghasemi HR, Mahmoudi M, Bahrami S, Pradhan B, Shirzadi A, Chapi K, Lee S (2019) Flood Spatial Modeling in Northern Iran Using Remote Sensing and GIS: A Comparison between Evidential Belief Functions and Its Ensemble with a Multivariate Logistic Regression Model. Remote Sens 11(13):1589. https://doi.org/10.3390/rs11131589
5. Bwala, H. B., Oladosu, R. O. & Nghalami, S. M. (2015). Application of Physical Planning Strategies to Flood Control in Maiduguri, Borno State, Nigeria. Research Journal of Environmental and Earth Sciences, 7(1): 1–8
6. Cabrera JS, Lee HS. Flood risk assessment for Davao Oriental in the Philippines using geographic information systembased multi-criteria analysis and the maximum entropy model. J Flood Risk Management. 2020;13: e12607. https://doi.org/10.1111/jfr3.12607
7. Das S (2019) Geospatial mapping of flood susceptibility and hydrogeomorphic response to the floods in Ulhas basin, India. Remote Sens Appl: Society and Environment 14:60–74. https://doi.org/10. 1016/j.rsase.2019.02.006
8. Detrembleur, S., Stilmant, F., Dewals, B., Erpicum, S., Archambeau, P., & Pirotton, M.. (2015). Impacts of climate change on future flood damage on the river Meuse, with a distributed uncertainty analysis. Natural Hazards. 77. 10.1007/s11069-015-1661-6
9. Doswell III, C.A. (2003). Flooding. Elsevier Science Ltd, Oklahoma, pp. 769–776. https://doi.org/10.1016/B0-12-227090-8/00151-2
10. Echendu, A.J. (2020). The impact of flooding on Nigeria's sustainable development goal, cosystem Health and Sustainability, 6:1, 1791735
11. Emberga, T. (2014). An assessment of causes and effects of flood in Nigeria. Scientific Research and Essays. 2 (7): 307–315
12. European Commission (2020). The EU Floods Directive. Retrieved from https://ec.europa.eu /environment/water/flood _risk/flood_risk.htm
13. Floodsite, 2008) Intensity of rainfall https://www.floodsite .net/juniorfloodsite/html /en/student /thingsto know/hydrology/rainfallintensity.html

14. Ghosh A, Kar SK (2018) Application of analytical hierarchy process (AHP) for flood risk assessment: a case study in Malda district of West Bengal, India. Nat Hazards 94(1):349–368. https://doi.org/10. 1007/s11069-018-3392-y
15. Jimme, M.A., Bashir, A, Adebayo, A.A. (2016) Spatial Distribution Pattern and Terrain Analysis of Urban Flash Floods and Inundated Areas in Maiduguri Metropolis, Borno State, Northeast, Nigeria. Journal of Geographic Information System, 8: 108–120. http://dx.doi.org/10.4236/jgis.2016.81011
16. Kazakis N, Kougias I, Patsialis T. (2015) Assessment of flood hazard areas at a regional scale using an index-based approach and Analytical Hierarchy Process: Application in Rhodope–Evros region, Greece. Science of the Total Environment 538:555–563.
17. Komolafe, A.A., Olorunfemi, I.E., Akinluyi, F.O. *et al (*2020*).* Enhanced flood hazard modelling using hydraulic, analytical hierarchical process and height above nearest drainage models in Ogunpa river basin, Ibadan, Southwestern Nigeria. Model. Earth Syst. Environ. **7**, 967–981
18. Komolafe, A.A., Adegboyega, S.A. & Akinluyi, F.O., A review of flood risk analysis in Nigeria. American Journal of Environmental Sciences, 11(3), pp. 157–166, 2015.http://dx.doi.org/10.3844/ajessp.2015.157.166
19. Lumbroso, D. Ramsbottom, D. & Spaliveiro,. (2008). Sustainable £ood risk management strategies to reduce ruralcommunities' vulnerability to £ooding in Mozambique J Flood Risk Management1(2008) 34–4
20. Magami, I.M., Yahaya, S. & Mohammed, K. (2014). Causes and consequences of flooding in Nigeria: a review https://doi.org/10.1007/s12145-020-00
21. Mayomi, Ikusemoran; Mohammed, Jimme Abba (2014). A decade assessments of maiduguri urban expansion (2002–2012): Geospatial Approach
22. Mirzaei S, Vafakhah M, Pradhan B, Alavi SJ (2020) Flood susceptibility assessment using extreme gradient boosting (EGB), Iran. Earth Sci Inf 14(1):51–67. https://doi.org/10.1007/s12145-020-00530-0
23. National Geographic (2018). Floods. Retrieved February 2018. Available via https://www.nationalgeographic.c om/environment/natural-disasters/floods/
24. Njoku, C.G., Efiong, J.,, Uzoezie, A.D., Okeniyi, F.O and Alagbe, A.O (2018). A GIS multi-criteria evaluation for flood risk vulnerability mapping of Ikom Local Government Area, Cross River State. Journal of Geography, Environment and Earth Science International 15(2): 1–17
25. Nicholls, N. (1987): Prospects for Drought Prediction in Australia and Indonesia. In: D.A. Wilhite and W. E. Easterling (eds.): Planning for Drought. Towa
26. Nkeki, F. N., P. J. Henah, & V. N. Ojeh. (2013.) "Geospatial Techniques for the Assessment and Analysis of Flood Risk along the Niger-Benue Basin in Nigeria." Journal of Geographic Information System 5 (2): 123. doi:10.4236/ jgis.2013.52013.
27. Norwegian Refugee council (2020) Torrential rains destroy shelters for displaced people in northeast Nigeria. https://www.nrc.no/news/torrential-rains-destroy-shelters-for-displaced-people-in-northeast-nigeria/
28. OCHA. (2012). Nigeria: Floods Situation Report No. 2. Retrieved From. https://reliefweb.int/sites/reliefweb.int/files/resources/Full %20Report_1141.pdf
29. OCHA (2019). NIGERIA: Floods in Borno, Adamawa and Yobe. OCHA Situation Report No. 2
30. Odihi, J.O. (1994): Flood Problems in Maiduguri. Paper presented at the Faculty Seminar Series, Faculty of the Social and Management Sciences, University of Maiduguri. Maiduguri, Nigeria.
31. Odihi, J.O. (1996). Urban droughts and floods in Maiduguri: Twin hazards of a variable climate. Berichte des Sonderforschungsbereichs, 268 (8), 303–319
32. Oladokun, V.O. & Proverbs, D. (2016). Flood risk management in nigeria: a review of the challenges and opportunities. int. J. of Safety and Security Eng., Vol. 6, No. 3 (2016) 485–497
33. Pradhan B (2009) Flood susceptible mapping and risk area delineation using logistic regression, GIS and remote sensing. J Spatial Hydrol 9:1–18
34. NPC (2008) National Population Commission, 2008. Maiduguri Projected Population. https://nationalpopulation.gov.ng/
35. Ogundele, J., and A. O. Jegede. 2011. "Environmental Influences of Flooding on Urban Growth and Development of Ado-Ekiti, Nigeria." Studies in Sociology of Science 2 (2): 89 http://dx.doi.org/10.3968/j.sss.1923018420110202.053
36. Ogunwumi, T. S., Waziri, E. S., & Udoh, J. C. (2021). Geospatial mapping of flood hazard using multi-criteria approach in fufore local government area, North Eastern Nigeria. Journal of Basic and Applied Research International, 27(3), 13–26. Available via https://www.ikprress.org/index.php/JOBARI/article/view/6445
37. Ojo, O. O., and J. A. Adejugbagbe. 2017. "Solid Waste Disposal Attitude in Sango Ota, Ogun State: Implication for Sustainable City Development in Nigeria." Journal of Environment and Waste Management 4 (3): 253–260.
38. Owusu, S., Mul, M.L., Ghansah, B. et al. (2017) Assessing land suitability for aquifer storage and recharge in northern Ghana using remote sensing and GIS multi-criteria decision analysis technique. Model. Earth Syst. Environ. 3, 1383–1393 (2017). https://doi.org/10.1007/s40808-017-0360-6
39. Ouikotan, R., J. V. Der Kwast, A. Mynett, and A. Afouda (2017). Gaps and Challenges of Flood Risk Management in West African Coastal Cities. Paper presented at the Proceedings of the XVI World Water Congress, Cancun Quintana Roo
40. Ozturk, D., Yilmaz, I., Kirbas, U. (2021) Flood hazard assessment using AHP in Corum, Turkey Evaluación de peligro de inundación utilizando AHP en Corum, Turquía. Tecnología y Ciencias del Agua 12(2):01–26. DOI: 10.24850/j-tyca-2021-02-08
41. Piantanakulchai, M & Saengkhao, N. (2003). Evaluation of alternatives in transportation planning using multi-stakeholders multi-objectives AHP modeling. Proceedings of the Eastern Asia Society for Transportation Studies. 4.
42. Pourghasemi HR, Pradhan B, Gokceoglu C, Mohammadi M, Moradi HR (2012) Application of weights-of-evidence and certainty factor models and their comparison in landslide susceptibility mapping at Haraz watershed, Iran. Arab J Geosci 6(7):2351–2365. https://doi. org/10.1007/s12517-012-0532-7
43. Ramakrishna, G., Gaddam, S. R. & Daisy, I. (2014). Impact of floods on food security and livelihoods of IDP tribal households: the case of Khammam region of India. International Journal of Development and Economics Sustainability, 2 (1), 11–24,
44. Rahmati O, Pourghasemi HR, Zeinivand H (2016) Flood susceptibility mapping using frequency ratio and weights-of-evidence models in the Golastan Province. Iran Geocarto Int 31:42–70. https://doi.org/ 10.1080/10106049.2015.1041559

45. Ryan, S., & Nimick, E, (2019). Multi-Criteria Decision Analysis and GIS. Retrieved from https://storymaps.arcgis.com/stories/b60b7399f6944bca86d1be6616c178cf
46. Samanta, S., Koloa, C., Pal, D. K., & Palsamanta, B. (2016a). Flood risk analysis in lower part of Markham river based on multi-criteria decision approach (MCDA). Hydrology, 3(3). https://doi.org/10.3390/hydrology3030029
47. Saaty TL (1980) The analytic hierarchy process: planning, priority setting, resource allocation. McGraw-Hill International Book Co, New York, London ISBN: 0070543712 9780070543713
48. Saaty TL (1990) How to make a decision: the analytic hierarchy process. Eur J Oper Res 48(1):9–26. https://doi.org/10.1016/0377-2217(90) 90057-I
49. Shettima, K.M. (2018). Geospatial assessments of flood liable areas in Maiduguri. An unpublished M.Sc. dissertation. Department of geography, University of Maiduguri.
50. Shettima, Mohammed Kaka & Mayomi, Ikusemoran & Daura, Mohammed. (2019). Geospatial Assessment of the Impact of Topography on Flood Vulnerability in Maiduguri. Retrieved from ttps://www.researchgate.net/publication/336458969_Geospatial_Assessment_of_the_Impact_of_Topography_on_Flood_Vulnerability_in_Maiduguri/citati
51. Security, C. O. H. (2013). "Building a Coordinated Approach to Flood Disasters in Nigeria." Nigeria. http://www.aapeace works.org.ng/documents/1412092739flood_coordina tion_workshop_rep_july_22,_2013.pdf
52. Toure, D. (2014). Resident/Humanitarian Coordinator Report On The Use Of Cerf Funds Nigeria Rapid Response Floods. Retrieved from https://www.unocha.org/cerf/sites/default/files/CERF/ RCHC%20Report%2013-NGA-001.pdf
53. UNOCHA (2019). Nigeria: Tens of thousands of people stranded by floods in north-east. Retrieved from https://www.unocha.org/story/nigeria-tens-thousands-people-stranded-floods-north-east
54. UNOCHA (2020). Nigeria. Retrieved from https://www.unocha.org/nigeria
55. Welde K, Gebremariam B (2017) Efect of land use land cover dynamics on hydrological response of watershed: Case study of Tekeze Dam watershed, northern Ethiopia. Int Soil Water Conserv Res 5(1):1–16
56. WHO (2021). Floods. Retrieved from https://www.who.int/health-topics/floods#tab=tab_1

Figures

Figure 1

Map of Maiduguri City

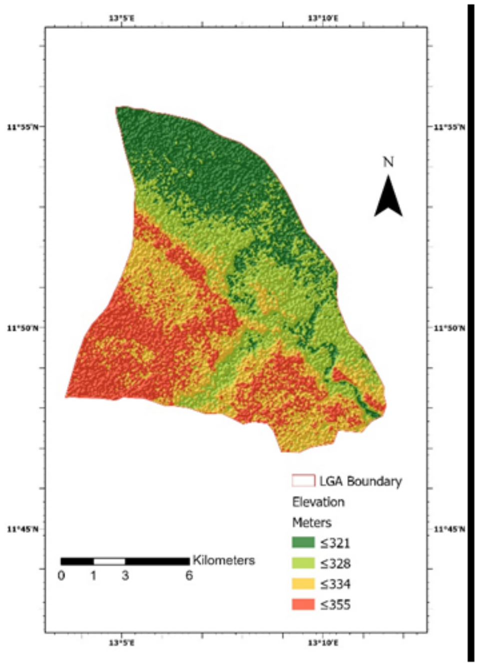

Figure 2

DEM

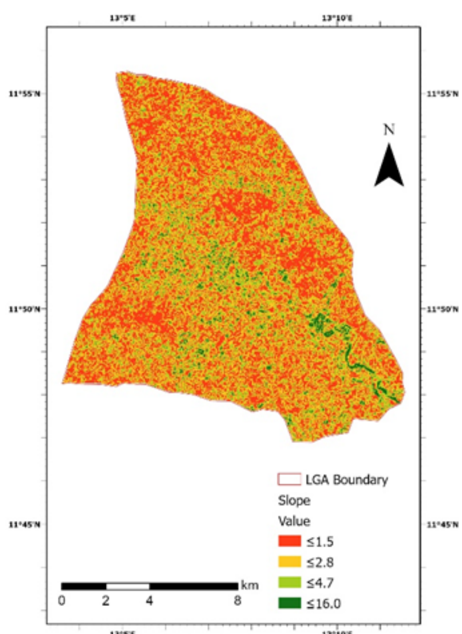

Figure 3

Slope model

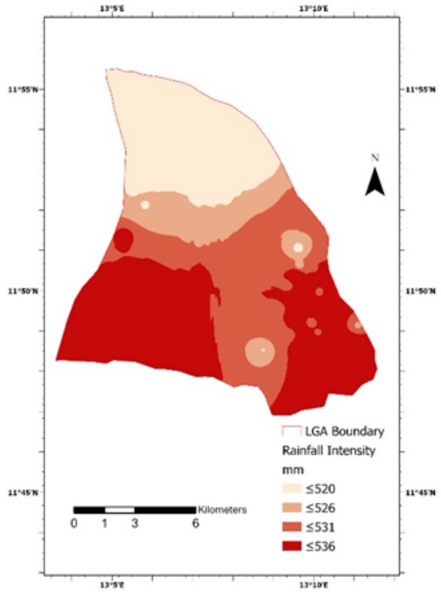

Figure 4

Rainfall volume distribution

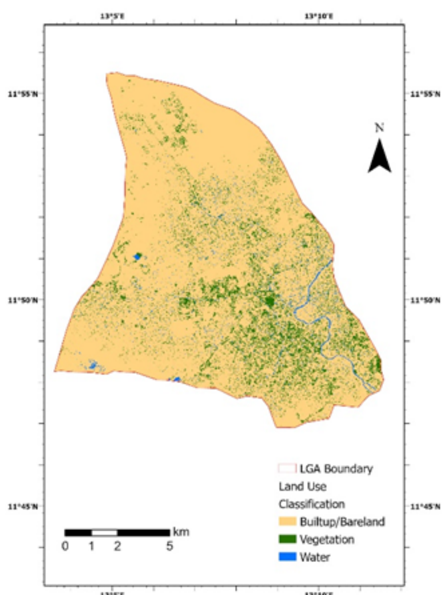

Figure 5

LULC map

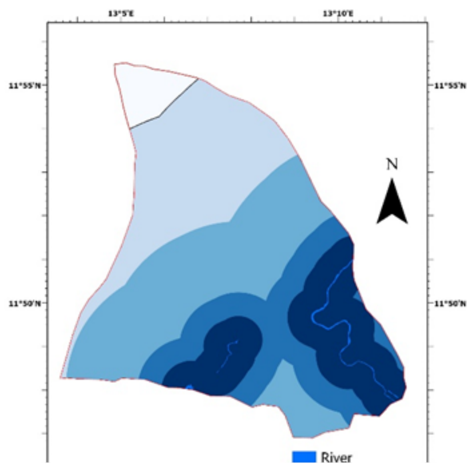

Figure 6

Buffer of big rivers

Figure 7

Buffer of small rivers

Figure 8

Flowchart for flood susceptibility assessment.

Figure 9

Reclass Big River

Figure 10

Reclass small river

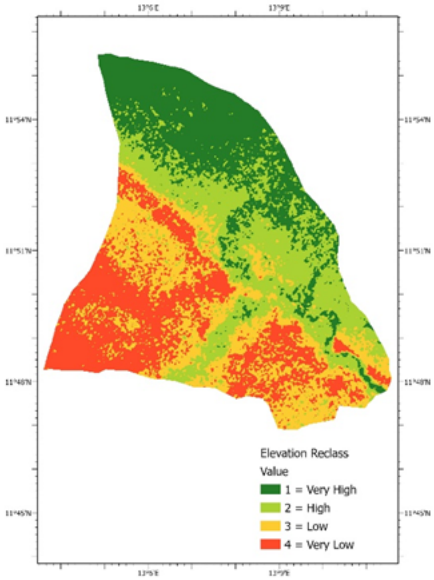

Figure 11

Reclass Elevation

Figure 12

Reclass Slope

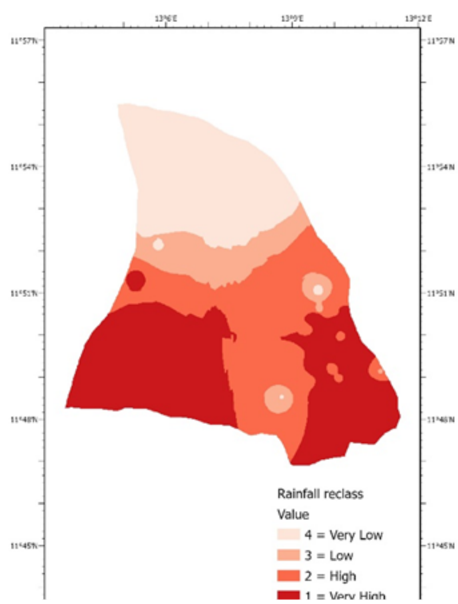

Figure 13

Reclass Rainfall

Figure 14

Reclass LULC

Figure 15

Flood susceptibility map of Maiduguri.

Figure 16

Proportion of IDP camps and their flood risk levels

Figure 17

Plate 1: Flooding in Stadium Camp, Maiduguri, June 2020.

Source: Norwegian Refugee Council (2020)

Figure 18

Plate 2: Flooding in GRA camp, Maiduguri.

Photo: OCHA (2019)