Multicriteria Index and Analytical Hierarchy Process on Flood Risk Assessment: Application in Niger State, Nigeria

Zulkhairi MD, Azman T, Ndanusa A

Abstract: Assessment of flood risks, especially extreme floods, is required for any location that is faced with recurrent flooding events for proper implementation of proactive measures. Therefore, this study presents a multi-criteria index-Analytic Hierarchic Process (AHP) approach to evaluate regional flood risks employing multiple flood causative factors by determining a Flood Risk Index (FRI) using a GIS-based spatial analysis. The developed framework utilized topographical, hydrological and vegetal factors to delineate the risks associated with various regions. The relative importance of each factor in determining flood vulnerability, as well as the severity of flood is associated with the weightage of such factors based on AHP. The framework has been applied to Niger State, situated within the north-central part Nigeria, which has been experiencing recurrent annual flooding events. The overall result revealed some vital details on the relative importance of each factors in inducing regional floods. Furthermore, the accuracy assessment conducted using regional flood inventory confirmed the reliability and validity of the developed Multicriteria Index and Analytical Hierarchy Process on Flood Risk Assessment (Mi-AFRA).

Keywords: Analytical Hierarchy Process, Flood Vulnerability, GIS, Sensitivity Analysis

I. INTRODUCTION

Flooding has become a serious issue in several parts of the world, and will relentlessly affect the way in which cities grow (Kulkarni, Mohanty, Eldho, Rao, & Mohan, 2014). Adversely, the current climate change has triggered major changes in rainfall pattern which in turn, has increased flood-related risks(Wang, Yi, Li, Wang, & Song, 2018). As a result, flood disasters will continue to occur in the future – one can never achieve complete safety (Kundzewicz, 2002). Yet, flood-related risks can be alleviated if an appropriate means of mitigation or preparedness is developed (Kundzewicz, 2002).

Broadly, flood risk mitigation approaches involve the identification of flood risk based on both structural and non-structural measures(Shah, Rahman, & Chowdhury, 2018; Sayers et al., 2013). In flood mitigation strategies, the structural measures are hard-engineered structures, such as dams and dikes, as commonly deployed in Malaysia, Nigeria, Bangladesh and India (Baghel, 2014a; Baghel, 2014b; Chan, Joon, Ziegler, Dabrowski, & Varis, 2018Warner, van Staveren, & van Tatenhove, 2018; Olukanni, Adejumo, & Salami, 2016). However, according to (Haque & Burton, 2005), these structural measures only address the physical risks of lives and property, and consequently, are inadequate to cover the full spectrum of disaster manage. Therefore, the need to consider non-structural means of flood management. To this effect, this paper examines some of the related works where non-structural management measures were adopted.

II. RELATED WORKS

Generally, assessing flood-related risks based on no-structural means is done using various approaches, depending on the volume of data sets, resources available and the time required (Büchele Kreibich, H., Kron, A., Thieken, A., Ihringer, J., Oberle, P., Merz, B., and Nestmann, F., 2006). For instance, in employing survey method, within the river of Kelantan, Malaysia, and urban regions of Abeokuta in Nigeria(M et al., 2014;Adelekan, 2011). These studies were conducted to delineate flood risks by administrating questionnaires within the affected regions. Even though regions of floodplain were identified from the responses obtained, hydrological and vegetal features enhancement was required. The use of hydrological and topographical features was equally recommended in order to enhance the interpretability of flood-risk assessment. Essentially, the analytical reliability in using these factors can greatly enhance the accuracy of decision that can be taken in flood management within the study area.

Similarly, in the study conducted by Ikusemoran, Kolawole, & Martins, (2014), based on non-structural measures to address flood-related issues in Niger State, which is equally considered the study area in this paper. In the aforementioned study, satellite imagery was also utilized assess various levels of flood risk. Using the elevation as the flood causative factor, various regions were classified based or their corresponding levels of risk to floods. In the classifications, the regions of Suleja which was classified to be non-vulnerable to flood risks have been experiencing floods for the past three years. Therefore, the accuracy of the classification was marred by the use of a single factor. Consequently, this study employed multiple factors in order

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to reveal the level of flood risk induced by other contributing factors.

As identified from these extant studies, the use of spatial data has been of a considerable contribution leading to flood disaster mitigation in various parts of the world. However, these studies are constrained by the use of limited factors in deriving insights to depict flood inducing factors, which has invariably undermined the level of accuracy in identifying regions that are prone to floods. Therefore, this study addresses this limitation by employing multiple factors to delineate flood plain within the study area.

III. MATERIALS AND METHODS

Study Area

The study area is located at the discharge point of the River Niger, which is 4160km long, the 12th longest river in the world, and the third longest in Africa (Unyimadu, Osibanjo, & Babayemi, 2017). Niger State is spanning around latitudes 8.02°N to 10.20°N and longitudes 3.38°E to 7.03°E (Ikusemoran et al., 2014). The State covers a landmass of 72,200.14 km^2 with 18,007.38 km^2, 24,181.04km^2, 20616.09 km^2 and 9,593.3 km^2 for valley, plains, upland and highlands respectively (Ikusemoran et al., 2014). The climate feature of the State is tropical monsoon with dry winter and humid summer, which makes rainfall relatively concentrated in summer, hence, leading to severe flooding events within this period.

Components of Mi-AFRA Framework

As earlier mentioned, various components of Mi-AFRA framework are based on spatio-temporal data sets, which were analyzed in order to derive useful insights on flood vulnerability using both Flood risk index (FRI) and Analytic Hierarchical Process (AHP)approaches as elaborated in the ensuing subsections.

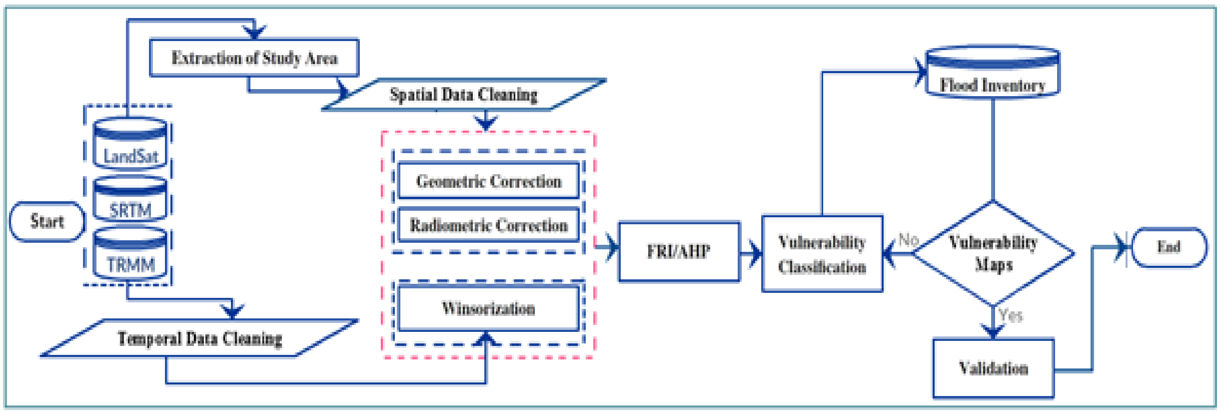

Fig. 1 Flowchart representing Mi-AFRA framework

From the above illustrative flowchart in Figure 1, the extraction of the study area was performed at the initial stage prior to performing geometric, radiometric and Winsorization corrections on spatial and temporal data respectively. The subsequent phases of the flowchart consist of the classification, FRI and AHP before the accuracy assessment using the framework validation approaches.

Flood Risk Index

Within the scope of this study, the formation of the proposed framework depends on Geographic Information System (GIS) packages with the aim of delineating regions that are vulnerable to floods. The proposed framework employed a multi-criteria analysis integrating an FRI, which is the output of sensitivity analysis. Essentially, the aim of the FRI is to aid in identifying regions that are highly vulnerable to floods and allows a comparative assessment using various flood causative factors as illustrated within proposed Mi-AFRA flowchart in figure 1.

Analytical Hierarchical Process

Broadly, the use of AHP provides an enhanced accuracy in decision-making when evaluating the influence of causative factors to flood vulnerability(Yahaya, Ahmad, & Abdalla, 2010).

In this study, the two primary GIS-based approaches; pairwise comparison approach i.e. AHP process as well as ranking approaches in the calculation of weights of the causative factors were adopted to determine the level of influence within posed by the various FCFs considered. Essentially, the pairwise-based matrix uses the pairwise comparisons as an input and provides the associated weights as output, while AHP provides a mathematical approach for interpreting this matrix into vectors for the various factors. These factors were also itemized in order of their influence in inducing floods in the study area as illustrated in Table 1.

Table. 1 Ranking of Flood causative factors

S/N	Causative Factor	Ranking	Weightage
1	Precipitation	1	40.8%
2	Slope	2	18%
3	Elevation	3	12%
4	Vegetation	4	9%
5	Flow Direction	5	8.2%
6	Flow Accumulation	7	7%
7	Topographic Wetness	9	5%

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From the values in Table 1, correspondingly, precipitation has 40.8% which was obtained from the model specification test conducted using the temporal data sets. Other values were subjectively assigned and validated by domain experts. The relative significance between the factors were created using 1-5,7 and 9 representing less important to the criteria with higher importance. The pairwise approach adopted used a matrix of 7 by 7, where elements at the diagonal equaled 1, as contained in Table 2 using a Normalized Matrix.

Consistency Check

Prior to the verification or consistency check, AHP-based eigenvector matrix was formed, which requires the need for the level of its consistency to be assessed. The needed consistency level is obtained using eq.1:

$$CR = \frac{\mathrm{CI}}{\mathrm{RI}} \quad (1)$$

Where:
CR: Ratio of consistency
CI: Index of the consistency
RI: Random Index.

From the given RI standard values, the results depend on the dimension of factors used with the corresponding values of RI. In the case of this study, seven (7) factors have been considered, which corresponds to 1.32. Analytically, the AHP restricts the values for the consistency ratio (CR) to be <0.1. While CI is calculated using Eq. (2).With λmax being the maximum eigenvalue of the comparison matrix, and *n* being the number of criteria. RI values are given in AHP predefined values.

$$CI = \frac{\lambda\mathrm{max} - \mathrm{n}}{\mathrm{n} - 1} \quad (2)$$

From the standard values in in AHP, CI was given byλmax-n =7.66, n=7 while RI = 1.32. Consequently, CR= 0.08. This validates the consistency of the weight since the value of CR is less than 0.1. Here, the significance of these results corroborates that even though precipitation is the most influential causative factor in causing floods within the study area, other factors equally contribute the vulnerability and severity of floods. Practically, the classification of flood vulnerability in the next section, which illustrated is by maps in Figure 2 further shows the spatial variability and severity of regional flood within the study area.

Table. 2 Normalized matrix

Causative Factors	Precip.	Slope.	Elevatio	Veg.	Flow Dir	Flow Acc	TWI	Total Row (Priority)
Precipitation	0.40	0.45	0.41	0.36	0.32	0.31	0.29	0.36
Slope	0.20	0.23	0.27	0.27	0.25	0.22	0.23	0.24
Elevation	0.13	0.11	0.14	0.18	0.19	0.18	0.16	0.16
Vegetation	0.10	0.07	0.07	0.09	0.13	0.13	0.13	0.10
Flow Direction	0.08	0.06	0.05	0.05	0.06	0.09	0.10	0.07
Flow Accumulation	0.06	0.05	0.03	0.03	0.03	0.04	0.06	0.04
TWI	0.04	0.03	0.03	0.02	0.02	0.02	0.03	0.03
Total	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**

IV. FLOOD RISK CLASSIFICATION AND MAPPING

This section discusses the morphometric components that reveal various classes of flood vulnerability in Niger State. Notably, the flood vulnerability associated with every region is influenced by the nature of the factor(s), as earlier prioritized in the preceding section using the AHP-based approach. Therefore, the precipitation, slope, elevation, NDVI, flow direction flow accumulation and TWI as shown in Figure 2, are the factors considered in this paper which were selected based on their associated influence within the study area as well as recommendations made by some related studies.

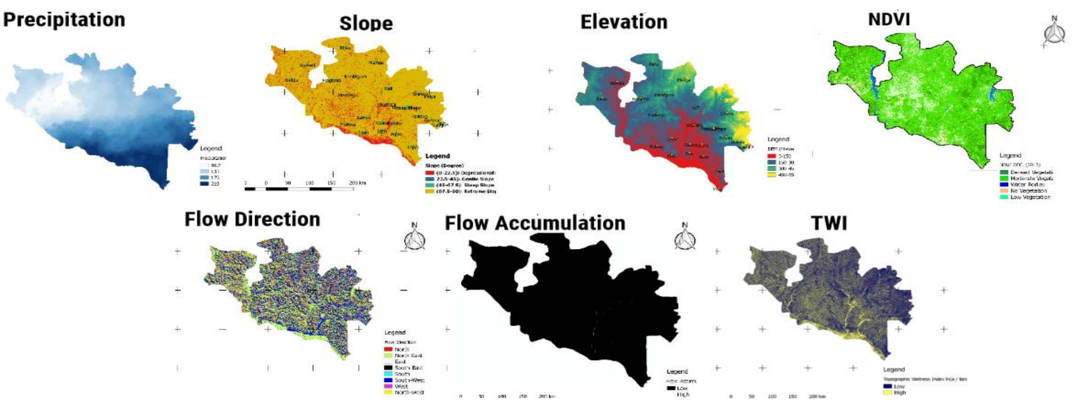

Fig. 2 Vulnerability classification and map

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Precipitation

Generally, precipitation data remains a vital factor to learn the pattern of rainfall which is required for hydrological cycle (Rahimpour, Zeng, Mannaerts, & Su, 2016). The intensity of precipitation immensely influences the severity of flood. This is because, the hydraulic conductivity depicts the property of soil or plants in relation to hydrological flows (Dunne, 1991).Essentially, the framework employed a Modified Fournier Index-based approach to determine the accumulation of precipitation. Explicitly, the Modified Fournier Index (MFI) represents the averaged sum of precipitation from each region. The regional accumulation of the precipitation was estimated by considering their relatively spatial distribution. As identified within the pre-processed precipitation data, the range of the precipitation is from 86.7mm to 219mm as shown in Figure 2, with the higher accumulation at the North-Central part of the study area.

Topographical Factors

Slope and Elevation

The slope and elevation of a surface have a significant influence topographically; it determines the direction as well as the volume of runoff on the surface, in addition to its contribution to stream flow. The values obtained for the slope factor ranges from 0°-22.5°, 22.5-45°, 45°-76.5° and 67°-90° representing high vulnerability, vulnerability, marginal vulnerability and non-vulnerability classes. While values for elevation stand between 90-128m, 129-256m, 257-384m and 385-512 also depicting high vulnerability, vulnerability, marginal vulnerability and non-vulnerability classes.

Vegetal Factor

Normalized difference vegetation index-based

Generally, Normalized Difference Vegetation Index (NDVI) plays an important role in controlling soil erosion. This is because, even an insignificant number of roots found on the soil can reduce the erodibility of an area when compared with regions without vegetation. As revealed by the pre-processed NDVI, Niger state is largely covered by moderate vegetation and partly dense vegetation, as illustrated in Figure 2. The features exude an associated level of vulnerability depending on either the region is covered with dense, low, moderate vegetation.

Hydrological factors

Flow Direction, flow accumulation and topographic wetness index

Specifically, the hydrological features denote the direction as well as the accumulation of water, which can potentially lead to a flooding event within the study area. In this paper, it was identified that the flow is mostly visible around the regions of Borgu, Bida, Lapai, Edati and Mokwa. While the flow accumulation is more visible around the regions of Gbako, Wushishi, katcha and Rafi. This identification of the direction and accumulation of flow, regions showing either of these features have an associated flood vulnerability. Finally, by using the Topographic Wetness Index (TWI), the identification of water content was performed. Evidently, regions of Bida, Agaie, Borgo and Agwara, while other regions have been attributed to a low water content. These low and high-water contents represent lower and higher floodplains respectively in the study area.

Practically, representations of these FCFs was further mapped in Figure 2. Essentially, the creation of maps is indispensable for regional prioritization, and are needed by disaster management agencies (Dasgupta, A., Grimaldi, S., Ramsankaran, R., & Walker, 2017).

V. SENSITIVITY AND FRAMEWORK VALIDATION

Within the approach based on sensitivity analysis, the initial random values of the indexes for AHP were replaced using the derived indexes, termed the "effective weights", which were determined by using the ensuing equation:

$$W = \frac{P_r . P_W}{V} 100 \quad (3)$$

Where:

W represents the effective weightage of each factor;

P_r represents the rating of the factors;

P_W represents the weightage of the factors;

V is the accumulated values of the index.

The effective weights contained in Table 3 were then utilized to estimate the revised Flood Risk Index within the sensitivity analytics leading to the generation of FRIS.

Table. 3 Effective weightage of sensitivity analysis

Factors	Min	Max	Mean(μ)	SD(σ)
Precipitation	6.6	45.9	12.0	3.2
Slope	6.1	50.5	25.6	7.8
Elevation	7.9	51.7	30.4	7.7
Flow Direction	2.2	21.6	7.4	3.4
Flow Accum.	1.1	16.1	5.0	3.0
TWI	4.3	27.3	15.5	3.9
NDVI	0.6	11.6	4.0	2.4

As contained in Table 3, the FRIS assesses the factors as well as their corresponding rating with the index of FRI with varied weights. Hence, it signifies an alteration of the Mi-AFRA approach, referred to as Mi-AFRA-S. FRIS is, therefore, valued within the range of diverse values of FCFs. In relation to the FRI, it shows the sensitivity of floods on various component of Mi-AFRA indexed by maps as illustrated in Figure 2. In addition to the sensitivity analysis, Flood Inventory (FI) was equally employed to ensure the validity of the developed framework.

In the validation phase of the framework using the FI, regional flood risk was classified spatially using the vulnerability maps as earlier illustrated in Figure 2. The accuracy of the classifications was assessed by the records of FI, with the events of floods that occurred – through the regions of high vulnerability to regions of marginal vulnerable from 2006-2017. In total, 42 events had occurred within regions classified to be highly vulnerable while no record of flood events associated with regions classified to be non-vulnerable as contained in Table 4.

Table. 4 Classes of flood risk and corresponding flooding event

Flood Risk	No. of flooding Events	No. of Regions
Highly Vulnerable	42	10
Vulnerable	16	5
Marginally Vulnerable	30	9
Non-Vulnerable	0	0

Table 4 above shows various classes of regions and the frequency of floods experienced regionally. Evidently, different vulnerability classifications illustrated in Figure 2, corroborate with the frequency of flooding events presented in FI. Thus, the accuracy of the classification has proven the correctness of the developed framework with the final output in Figure 3.

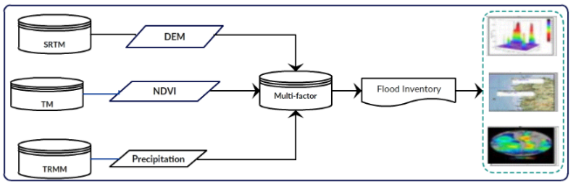

Fig. 3 Mi-AFRA Framework

VI. CONCLUSION

Flood risk assessment and mapping which classify floodplains, are required in flood mitigation and proper decision-making. Thus, Mi-AFRA framework was developed using multiple FCFs. The factors considered are topographical, hydrological and vegetal features. The associated level of influence of these factors was estimated by the AHP. Precipitation has the highest value of weightage, since it is the most inducing flood causative factor. The implementation of the developed framework in Niger state has revealed various regions that are vulnerable to floods as well as their corresponding levels of vulnerability.

Ultimately, the accuracy and the reliability of the framework was ensured using a decadal flood inventory data. Even though NDVI was used to show the nature of anthropogenic activities and other factors, such as population density and settlement information can further enhance insights on the downstream identification of flood risk for a sectorial flood mitigation approach in future studies.

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