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TOPOGRAPHIC-BASED FRAMEWORK FOR FLOOD VULNERABILITY CLASSIFICATION: A CASE OF NIGER STATE, NIGERIA

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Abstract: *Flood vulnerability classification often provides insights on measures aimed at mitigating flood-induced disasters, by revealing the factor(s) contributing to regional flood vulnerability. In this present study, the regional flood vulnerability classification within Niger State, Nigeria, which is overwhelmed by annual flooding event is considered as the study area. The study required the pre-processing of spatial data sets within a Quantum Geographic Information System (QGIS) environment to extract topographic flood causative factors depicting the levels of flood vulnerability in various regions within the study area. The extracted features were employed to classify regions based on their relative vulnerability to potential floods. In assessing the accuracy of the obtained results, Flood Inventory (record of flooding events) from 2006-2017 was utilized. The results showed that regional vulnerability classification was accurately represented using the slope than the elevation feature. Thus, giving preference to the slope-based classification to provide guidance for identifying the most reliable and suitable practical means of regional flood mitigation within the study area.*

Keywords: *Digital Elevation Model, GIS, Slope, Spatial Data Pre-Processing.*

Introduction

Flood is considered to be one of the most devastating and frequently occurring natural hazards globally. Impacts of flood disaster on the society and its effect on sustainable development are overwhelming in recent years (Komolafe, Adegboyega, & Akinluyi, 2015). Within the last decade, many countries have experienced an upsurge of flooding events, which is attributed to the current climate change. With Asia experiencing most flooding events due to the climate change, while Africa is generally associated with poor implementation of flood control policies. Thus, presenting the need for an effective and a reliable analytical approach to understand the nature of the vulnerability for appropriate decision-making aimed at mitigating the associated impacts (Thapa & Bossler, 1992). In order to perform an effective flood analysis, there is the need to have a reliable information depicting the extend of the regional vulnerability to floods (Tarekegn, Haile, Rientjes, Reggiani, & Alkema, 2010).

At present, several means of proposing solutions in flood management have been proffered by some studies. Nonetheless, these studies also presented certain levels of limitations; ranging from the use of a single factor in classifying flood vulnerability or inability to ascertain the level of accuracy by means of accuracy assessment as elaborated in the ensuing section.

Literature Review

In view of mitigating the impacts of floods, vulnerability assessment within the urban region, a study was conducted by Adelekan, (2011). This was attained with the aid of administrating questionnaires to respondents over affected regions. The results obtained indicated that, approximately 50 percent had witnessed flooding events in the past. Majority of the respondents (85 percent) expressed their concern over the non-availability of warning measures. To this effect, (Adelekan, 2011) recommends the need for a proficient approach in flood analysis for better understanding of flood vulnerability which will in turn, enhance the level of proactive measures to be taken in mitigating the potential impacts at vulnerable communities.

In a similar approach, a geological data set was used to identify the lithological attributes of Kota Bharu, Kelantan (Khan et al. 2014). Questionnaires were administered to some inhabitants, with 85.63 percent admitting being affected by flooding events on annual basis. This study recommends the identification of changes in water body to prevent flood-induced impacts. The recommendation made in this study involves the use of hydrological and vegetal features from satellite imageries, which can reveal the pattern of vegetal stratification and water content within the regions for better decision-making as adopted in (Martinez & Le Toan, 2007). Essentially, accurate information depicting the extent of water content is crucial in flood management(Smith 1997). Often, this information is difficult to produce using the aforementioned traditional survey techniques as water contents can be fast moving as in floods, tides, and storm or may be inaccessible(Jain, Singh, Jain, & Lohani, 2005). The synoptic, repetitive nature of satellite remotely sensed data enables monitoring of water bodies over large regions of land (Jain et al., 2005). Therefore, as a basis for the present research, studies based on satellite image pre-processing were reviewed.

While these analysis based on survey seemed constrained in providing the required means of flood mitigation, the use of Geographic Information System (GIS) was employed in (Abah & Clement, 2013). Data used consisted of field observation, drainage map, topographic map, land use, land map and precipitation data to identify the occurrence of a flood as well as the vulnerable regions. Although, the use of GIS and various sets of data yielded a certain level of accuracy in flood assessment, the study further recommends the use of satellite imageries to be pre-processed in order to enhance the scope of the study.

In assessing and mapping the level of havoc caused by flooding event, spatial imageries were pre-processed by Dumitru, Cui, Faur, and Datcu, (2015), where Imageries representing both pre-event and post-event were captured. The pre-processed features revealed damaged and non-damaged regions needed for post-disaster assessment. Interestingly, the result showed about 30 percent of the area was affected by flood. Although, this pre-processing of spatial data in this study generated a desired result by identifying vegetal and settlement features, inclusion of other features such as hydrological, and topographical features. This would have considerably enhanced the result beyond damage assessment to vulnerability identification which would have be employed for flood management in the future. In the same vein, while analysing the regional flood vulnerability within the study area, spatial data was pre-processed to identify the variability of regional flood vulnerability. Regions were classified into Highly Vulnerable, Vulnerable, Marginally Vulnerable and Non-Vulnerable (Ikusemoran, Kolawole, & Martins, 2014). Evidently, the result obtained from this study presented a relative level of accuracy. Nonetheless, the regions (Suleja) classified to be non-vulnerable, have continued to experience severe floods in the past two years as contained in the flood inventory data set. Therefore, instead of the regional vulnerability assessment based on an elevation classification alone, this present research pre-processed other causative topographic factors to enhance the level of accuracy in analysis on regional vulnerability within the study area, as recommended within the study on flood inundation modelling, which was conducted by Teng et al. (2017).

Generally, the data sets employed within the anthropogenic context, especially for impervious surfaces, such as buildings are crucial not only for environmental studies, but also in flood vulnerability studies (Asad, Ahmad, Ali, Mehmood, & Butt, 2017). To this effect, a study based on these data sets was conducted for an automatic building extraction needed to learn the hydrological pattern, (Hung, James, & Hodgson, 2018). Despite the level of success recorded within the scope of this study, the need to reveal the physical characteristic was identified. Therefore, this present study classified the slope of the study area to have a holistic knowledge of the topographical feature of the terrain. Essentially, not only does slope influence the timing of runoff, but it equally influences the volume of infiltration. Low gradient slopes are more susceptible to floods when compared to slopes of high gradient. Consequently, the slope is another vital factor to consider in the classification of flood vulnerability, (Asad et al., 2017), as adopted in this study.

The Study Area

Niger state is situated between latitudes 8.02◦N and 10.20◦N and longitudes 3.38◦E and 7.03◦E (Figure. 1). The population conducted in 2006 was estimated to be 3, 954,772 (Ikusemoran et al., 2014). The State covers a landmass of 72,200.14km2 with 18,007.38km2, 24,181.04km2, 20616.09km2 and 9,593.3km2 for valley, plains, upland and highlands respectively (Ikusemoran et al., 2014). The climate exudes two distinct seasons the dry and rainy seasons. The State has a variation of annual rainfall from 1,66mm in the south while 1,200mm within the northern regions. The annual rainy season lasts between 150 to 210 days throughout the year (Ikusemoran et al., 2014). Even though the state is mostly identified by ferruginous, hydromorphic and ferrosols are other two soil types that constitute part of the soil within the State (Ikusemoran et al., 2014).

Broadly, Niger state is fortunate not to be experiencing any natural disasters such as earthquake. However, the most frequent and detrimental natural disasters in Niger State are caused by annual floods which affect both lives and properties within the vulnerable areas. Report of flood inventory gathered from the Niger State Emergency Management Agency (NSEMA) indicates that more than 86% of the regions within the state are vulnerable to flooding events. With a very severe level of damages ranging from loss of lives, destruction of bridges as well as houses amongst others. The occurrence of floods in the study area is mainly due to heavy rainfall which is normally experienced between the months of May to October (Makun, Gbodi, & Akanya, 2007).

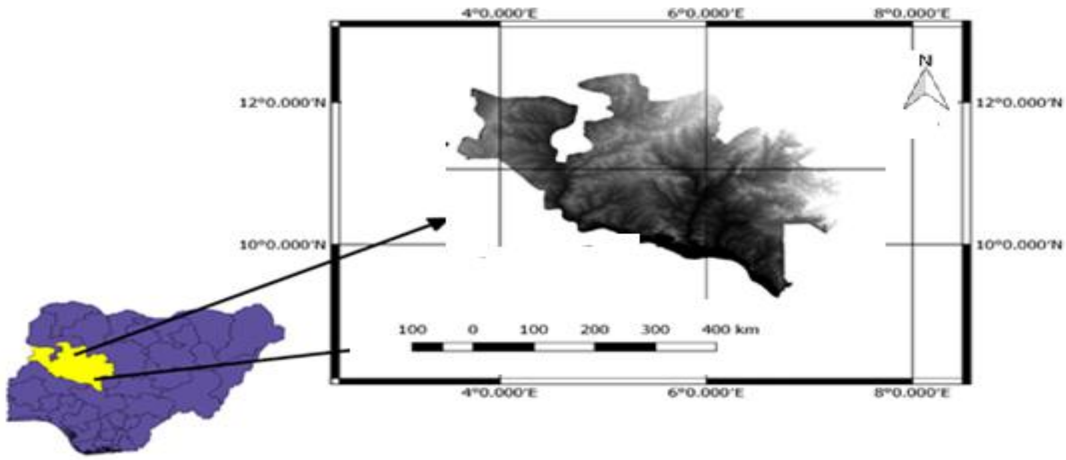

Figure 1. Raster Imagery Representing the Study Area

While regional flooding events are mainly associated with heavy precipitation, the mostly affected regions are identified to be situated within low elevated surfaces of the State (Ikusemoran et al., 2014). Therefore, this study identifies the influence of topographic features needed for an accurate classification of regional flood vulnerability with the state as illustrated in the framework in the ensuing data methodological section.

Data and Methodology

A key contribution of the study is in its multiple use of flood causative factors and the method used in identifying regional flood vulnerability as illustrated in Figure 1. The study is based on DEM and Slope features. The use of DEM was needed to demonstrate the inherent limitations in employing DEM for flood analysis similar to the study by Ikusemoran et al. (2014). While slope was employed so that original and new data are generated for our analysis on regional flood vulnerability aimed at addressing the limitation in the existing studies

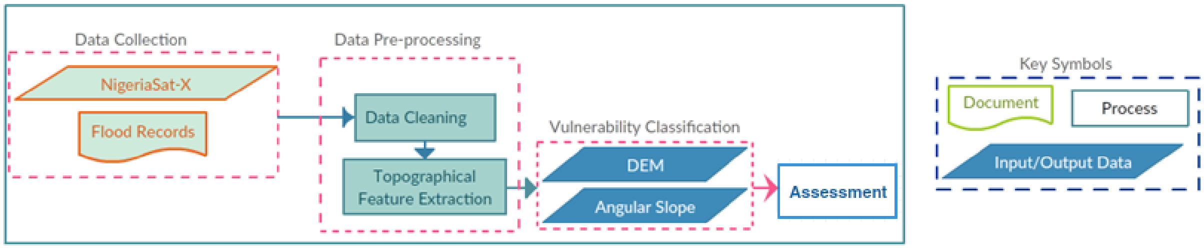

Figure 2. Topographic-based Flood Analytical Flowchart

As earlier discussed, this study is entirely based on the utilization of topographic data sets for regional flood vulnerability identification and classification. Based on the framework, the processes involved are outlined in following subsections:

Data Collection

Generally, the approaches of GIS involve the collection, visualization and analysis of heterogenous spatial data (Thapa & Bossler, 1992). The proposed framework uses geo-spatially referenced sets of data as input for deriving the required parameters, which includes most data types supported by QGIS, involving shape file and the NigeriaSat-X. The digital maps of topography from NigeriaSat-X was the base data used within the framework. In practice, the utilization of this imagery is due to its resolution which is at 22m needed to accurately represent the actual topography of the study area.

In addition, the records of flooding events or flood inventory consisting the occurrence of floods from 2006-20016 in all the regions of the study area were collected. The collection of data sets was done from a data-intensive sources. The uncertainty of these data is intrinsic (J. Chen et al., 2013). Therefore, the effective means of cleaning the data needed to be implemented before the utilization was required in order enhance the efficiency of the framework to yield an accurate analytical result (H. Chen, Ku, Wang, & Sun, 2010).

Data Pre-processing

Data pre-processing represents one of the crucial phases in knowledge discovering processes (Guo et al. 2015;Schumann et al. 2007). The processes involved in pre-processing take more than 50 percent of data analysis processes (Baraldi & Baraldi, 2009). Generally, raw data sets as in the case of this study usually comes with several flaws, such as noise and distortions (Ramírez-Gallego, Krawczyk, García, Woźniak, & Herrera, 2017). Therefore, performing proper pre-processing which includes cleaning and transformation tasks greatly enhances the quality and the reliability of knowledge discoveries and decision (Ramírez-Gallego et al., 2017).

Data Cleaning

After the collection of the spatial data sets, NigeriaSat-x in addition to Shapefile (.shp) were used to clip the study area, while other regions were masked prior to the cleaning processes involved in the geometric corrections, as depicted in Figure 1. Essentially, data cleaning or data scrubbing is the technique of identifying and correcting (or removing erroneous outliers from data set). The technique also assuages the issues of inconsistencies and missing values ("No Data") (Rahmati, Zeinivand, & Besharat, 2016). Specifically, cleaning a raw data is very important because irrespective of the source of a data, raw data cannot be error-free regardless of the level of prudence adhered during the collection of the data (Liu, Tk, Thomas, & Hou, 2016). Therefore, in this study, the spatial data was geometrically corrected. Procedurally, various imagery formats were initially standardized from the originally collected formats. This process enables the integration of the various data sets into the GIS tools for pre-processing processes. Then the satellite imageries were first pre-processed (filling local depressions), the sinks and imperfections of DEMs were identified and filled accordingly. This is because if not done, they will cause the surface flow to disappear and invalidate the water balance. After this preliminary correction, the images were geo-referenced to Universal Transverse Mercator (WGS84- Zone 32N) and a common window covering the same geographical coordinates was then extracted from imageries prior to the extraction processes as elaborated in the ensuing subsection.

Feature Extraction

Feature extraction has been regarded the most essential aspect where pattern identification and image analysis are needed (Liu et al., 2016). The main aim in processing voluminous images is feature extraction to obtain both descriptive as well as interpretive knowledge of an event (Wang et al., 2016). Since flood vulnerability is mostly associated with the topographical pattern, DEM and angular slope features were extracted depicting the terrestrial characteristics of the study area. This was done by employing the cleaned spatial data as an input data, while required features to be extracted generated as the output data sets. The extracted features were further vectorised using QGIS-Grass module, while the generated outputs were classified into four varied classes (Figures 3 and 4), representing various levels of regional flood vulnerability based on the effects of both DEM and Slope to aid general the analytical results.

Vulnerability Classification

As earlier stated, various studies have been conducted within and beyond the study area in flood-related domains. However, these studies have been constrained due to the poor identification of regional flood vulnerability especially, using the DEM. Therefore, this paper presents analytical results in order to identify the limitations of the existing studies as well as the strength of the present study using the effects of both DEM and Slope on regional flood vulnerability within the study area.

Effect of DEM

The effect of DEM on regional flood vulnerability varies depending on the level of elevation. Where a region exudes lower elevation, the vulnerability to flood is high and vice versa (Rahmati et al., 2016). Illustratively, Figure 3 explains the influence of elevation to flood vulnerability by classifying various regions in the study area and their respective levels of vulnerability.

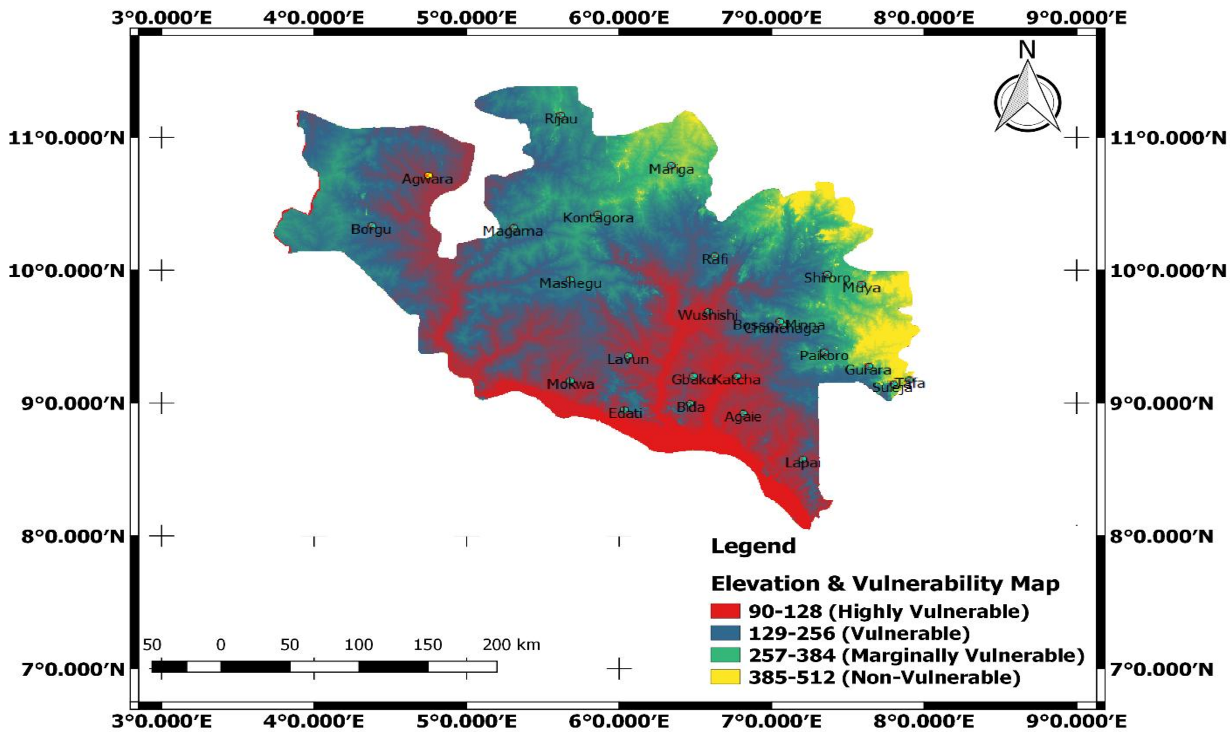

Figure 3: DEM-based Vulnerability Classification

The value of elevation obtained for various regions represents the gradient of the surface within the region recorded in metres(m). Within the region of Katcha, which was marked by the lowest level of elevation. The obtained value was 90.2457m. While Tafa possesses the highest elevation value at 511m as shown in Table 1.

Table 1: DEM-based Vulnerability Classification

Regions							Elevation (m)	Class
Bida		**Gbako**			**Katcha**		90-128	Highly Vulnerable
123.0762		406.2143			90.2457			
Agaie,	**Agwara,**	**Edati,**	**Lapai,**	**Lavun,**	**Mok.**	**Wushi.**	129-256	Vulnerable
117.6239	161.5762	159.9411	183.7931	161.9863	169.6565	145.1833		
Borgu,	**Bosso**	**Chan.**	**Kont.**	**Mag**	**Mashegu**	**Paiko.**	257-384	Marginally Vulnerable
262.6028	270.5563	252.5918	330.9187	295.8828	268.456	307.8022		
Rijau	**Shiro**	**Gurara**	**Mariga**	**Munya**	**Rafi**			
365.2663	280.1323	127.6221	430.8329	415.7286	288.6829			
	Suleja				**Tafa**		385-512	Non-Vulnerable
	451.6622				511.152			

From the classification based on the influence of elevation, the three classes of vulnerability as adopted in (Ikusemoran et al., 2014), have an influence in various regions of the study area. Suleja and Tafa were considered non-vulnerable. However, due to the unreliability of the results obtained using the elevation values as earlier stated in the previous section, the angular slope must be regarded as a causative factor. Most importantly, slope plays a vital role in identifying the velocity as well as vertical percolation in inducing flooding events (Rahmati et al., 2016). Therefore, this present research identifies the regional vulnerability based on the slope as described as follows.

Effect of Slopes

The slope of a surface plays a significant influence topographically as it determines the direction as well as the volume of runoff on the surface, in addition to its contribution to stream flow. Specifically, when the degree of slope increases, flood vulnerability within regions of lesser degree of slop increase (Rahmati et al. 2016; Tehrany et al. 2015). In this paper, the angular slope which is measured in degree (^{0}), was further extracted from the imagery in order to identify the steepness of a slop and the corresponding level influence it has in causing regional flood. This is essentially was needed since it determines the flow of water.

Notably, as classified within the extracted feature, the slope at depression level (0-22.5°) causes a quick flow of water which greatly initiates floods within the study area. Inversely, extreme slope (67.5 - 90°) reduces the flow of water. However, steep and extreme slopes cause flood in regions with lower slopes while depression slope causes water logging. Broadly, low gradient or depression slopes are more vulnerable to flooding events compared to slopes of steep and extreme forms because water from rain or from rivers always accumulates within regions marked by low gradient (depression) pattern. As shown in Figure 3.

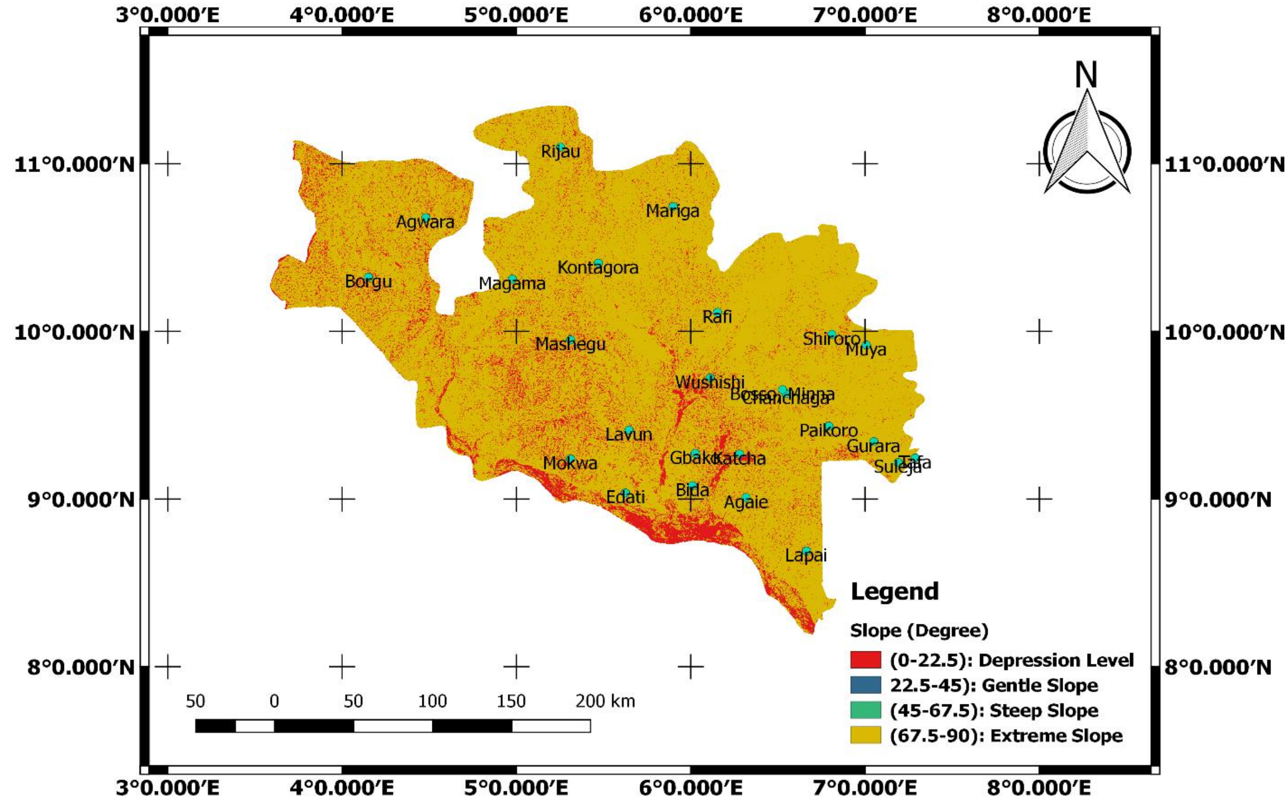

Figure 4: Slope-based Vulnerability Classification

As illustrated above, a vulnerability map based on the slope factor representing the study area was further generated from regional slope. The classification of the vulnerability-based slope has been classified into the ranks of Depression (Highly vulnerable), Gentle slope (Vulnerable), steep slope (Marginally Vulnerable) Extreme slope (Non-Vulnerable). For the study area, the vulnerability map based on the slop shows that Niger State lies largely between depression slope and steep slope. By implication, virtually all the regions have their peculiar traits of flood vulnerability. However, regions, situated within the depression slope are more exposed to flood vulnerability as a result of the flow being directed from the regions of extreme slope with a high velocity. The levels of vulnerability based on regional slope is classified in Table 2.

Table 2: Slope-based Vulnerability Classification

S/N	Regions	Slope (°)	Class
1	Mokwa, Mashegu, Borgu, Lavun, Agawara, Wushishi, Katcha, Gbako, Edati, Gurara	0-22.5	Highly Vulnerable
2	Agaie, Bida, Rijau, Bosso, Chanchaga	22.6-45	Vulnerable
3	Shiroro, Munya, Suleja, Lapai, Paikoro, Kontagora, Magama, Rafi, Tafa, Mariga	46-67.5	Marginally Vulnerable
4	N/A	67.6-90	Non-Vulnerable

Accuracy Assessment

Despite the relatively uniform level of regional vulnerability to a certain extent, there is a clear trend of high vulnerability within the regions of Katcha, Lapai, Edati and Borgu. This can be attributed to the low level of elevation and the depressional degree of angular slope. Similarly, as earlier mentioned, regions identified to be non-vulnerable as identified using elevation values specifically, regions of Suleja have continued to experience flooding events for the past two years as contained in the Flood Inventory data sets illustrated in Figure 4. In addition, this region was further confirmed to be vulnerable to flooding events with the results acquired from the slope. A possible explanation is that spatial distribution of regional vulnerability could be associated to its role in identifying the velocity as well as filtration capable of causing flooding event as stated by Rahmati et al., (2016).

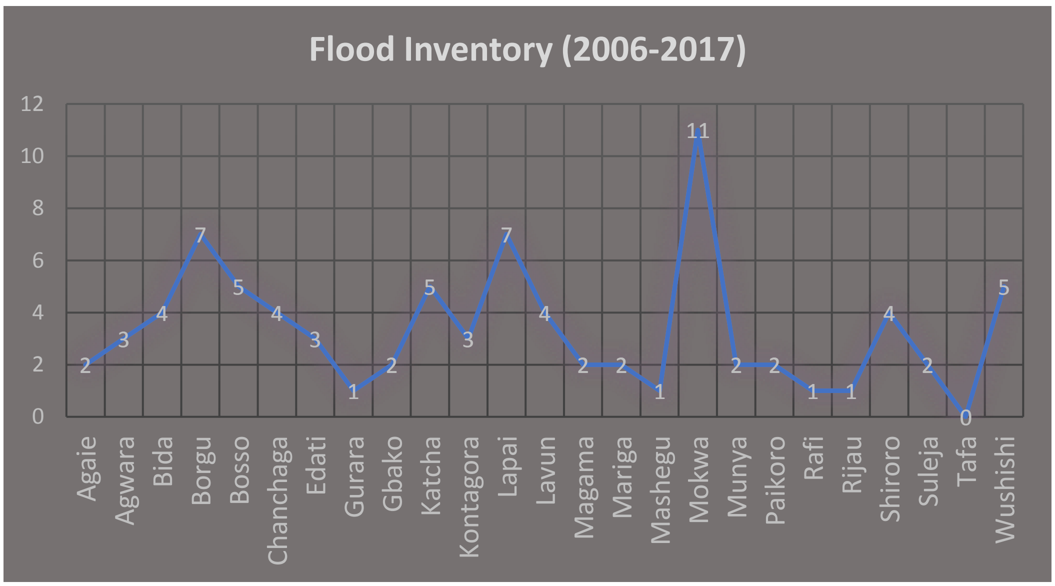

Figure 5. Records of Regional flooding events (2006-2017)

As illustrated in Figure 4, the regional flooding events recorded from 2006-2017 showed all the regions have experienced flooding events except the region of Tafa. Contrary to the result obtained using DEM as well as the study conducted by Ikusemoran et al. (2014). This is a further evidence that slope-based vulnerability analysis generates more accurate result as against the elevation-based study conducted for flood vulnerability analysis within the study area by Ikusemoran et al. (2014). Nonetheless, the overall results the classifications obtained from both causative factors were closely similar. Accordingly, variations in the of patterns depicting the classifications were not unlikely. Hence, the justification for regional vulnerability classification using multiple causative factors in order to have a holistic assessment of the vulnerability for appropriate decision-making needed in disaster mitigation for any potential flooding event within the study area.

Conclusion

This study has shown that several studies have been conducted on flood vulnerability and risk assessment in different parts of the world using various methods and scopes. Most of these studies focused on the socio-economic and physical qualitative vulnerability facets of flood hazards, using non-spatial data sets (Survey), while some only focused on a single flood causative factor which could not reliably identify flood vulnerability. The use of topographic feature to derive elevation and slope in this study provided a more accurate result in identifying regional flood vulnerability as classified within the study area. Thus, it is reasonable to infer that regional flood vulnerability identified by the slope is more accurate compared to the result obtained from elevation classification. While other forms of induced regional flood vulnerability can be classified in further studies by focusing on additional flood causative factors, such as the hydrological and vegetal factors, the approaches demonstrated in this paper have essentially highlighted the practical prospects, as well as the limitations in employing DEM in regional vulnerability mapping which can be adopted in a data scarce environment.

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