Categorization of Conditioning Variables for Pluvial Flood Risk Assessment

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Abstract: Flooding has been a recurring decimal in different continents and it accounts for about one-third of all natural disasters in terms of number and economic losses. Specifically, pluvial flood has contributed immensely to flooding globally. Several conditioning variables have been identified from literature for flood detection and prediction but there has been scant research in the selection of condition variables for flood prediction. The aim of the study is to undertake an integrative review method to categorize and determine the appropriate conditioning variables for a pluvial flood. The identified literatures were analysed with the aggregation of each review to create a comprehensive data description. The identified conditioning variables from literatures were categorised into three (3) factor categories with a total of sixty-three (63) descriptors, which were then prioritized on the basis of the degree of interdependency. The highest priority category identified was hydrological. This was followed by topographical and anthropological. This study identified conditioning variables under hydrological factors as the most important of the three (3) categories as it relates to pluvial flood occurrence and risk assessment. Hydrological factors have a great impact on the intensity of the pluvial flood before considering variables under the remaining factors. This finding is a step towards providing a clearly defined category to effectively inform the preparation for the development of the pluvial susceptibility map using machine learning.

Keywords: Anthropological**,** Conditioning Variable, Degree of Independency**,** Hydrological, Pluvial Flood, Risk Assessment**,** Topographical,

1. INTRODUCTION

The progression of human society has always depended on the passage of water and the development of any society depends on their capacity to control the water resources and risks attached to its existence [1]. The future of human society has been tested by the increasing number of settlers, untenable suburbanization and spatial advancement [2], infrastructural ageing [3] and in addition the change in climate which have given rise to a different level of risk from water-related natural disasters as a result of the above-mentioned challenges. The periodical occurrence of emergency situations represent an important issue for mankind.

Flooding has become a recurring decimal in different continents and it accounts for nearly one-third of all-natural disasters in terms of number and economic losses [4]. Flooding is an overflow of a wide scope of water that sinks below the surface of the earth. This may result from a deluge of water within a body of water, such as a river or lake which result in some of the water escaping its usual boundaries. Various types of a flood can affect urban areas and some of them may be more applicable to some regions than others. These floods are mainly classified into four types, namely coastal, fluvial, pluvial and flash floods. Other types are riverine flood, estuarine flood, single event flood, multiple event flood, seasonal flood and the flood caused by dam failure [5]. Floods are triggered by conditioning variables which are referred to as the factors that influence the occurrence of flood. There has been scant research into the selection of flood conditioning variables during flood risk assessment. A clear understanding of the selection would be of benefit in flood risk management by systematically informing the preparation of susceptibility mapping of a particular area. To proffer solution to this problem, a research literature review was conducted to better categorize and determine flood conditioning variables according to the priorities for pluvial flood risk assessment.

2. RESEARCH METHODS

This study was conducted by using an integrative review method. This method was selected based on its effectiveness in defining concepts [6] [7]. It gives room for the addition of a range of sources such as qualitative and quantitative research data except for opinion and grey literature [6]. The method also allowed specific aspects of previous studies to be evaluated critically and methodically [8]. To achieve this systematically, the study was completed in five stages: problem identification, literature search, data evaluation, data analysis and presentation [6]. Each stage is discussed in the following sections.

2.1 Problem Identification

The selection of flood conditioning variables in the most significant stage in the development of the final flood susceptibility map, which is not clearly defined, described and categorized to effectively informs the preparation for the development of the final map. Various authors used the most relevant and repeated used condition variables in previous studies. There still exists a lack of framework or an agreement for universal guideline in selecting the conditioning variables [9] [10].

2.2 Literature Search

This will be conducted over three stages. The first stage focused on clarifying the search term in google scholar alerts. The second stage was to extend the search to other research databases and the last stage was the selection of articles for analysis on the basis of specific inclusion and exclusion criteria.

2.2.1 Refining the search terms

The search terms were determined through a process of refining an alert in google scholar between November 2018 and December 2019. Google scholar was selected because it has incentives for quality, visibility and open access [11]. Based on this process of refining, the following search alerts were created: “Pluvial Flood”, “Flood Prediction”, “Flood conditioning factors”.

2.2.2 Research Databases

Electronic searching, hand searching and citation tracking were carried out within Elsevier, Taylor & Francis, John Wiley & Sons, Springer, MDPI and Copernicus. Based on the area of research, the search was limited to flood and pluvial flood. This approach ensured that the search was tailored to each research database which increased the efficiency and accuracy. During the search process, several terms were combined to form key terms combinations. For example, first, there is a term referring to conditioning such as explanatory, the second term refers to various synonyms of factor and the third term refers to multiple forms of a flood. The combination of the three terms was used to identify the potentially relevant pieces of literature from the research databases.

2.2.3 Selection Strategy

The selection of articles was conducted over three stages after retrieval from the research database. This included the selection of articles based on the title, followed by the review of abstract and then a full-text investigation. An article was considered relevant if the inclusion criteria were attained, which included pluvial flood, urban flood, factors, variables and discussing how conditioning variables can be categories. Articles were excluded if they did not include pluvial flood, urban flood, factors, variables and discussing how conditioning variables can be categories.

2.3 Data Evaluation

This was conducted by organizing the data, reading, memoing and data description [12]. The method for each was as follows:

- Data organization: After being sourced, the articles were saved electronically into a folder and hard copies were printed out.
- Reading and memoing: the articles were read and notes were written through the combination of the hand using a pen and electronic method. Details gathered were captured electronically according to key phrases, ideas and concepts.
- Data description: Personal description for each article was developed which included the description of articles into 4 types namely literature review, quantitative, qualitative and mixed methods. This was followed by describing identified conditioning variables in each article in categories.

2.4 Data Analysis

The conditioning variable data were analysed into categories and then the degree of interdependency index was calculated. The categorization included the grouping of conditioning variable categories as identified and a description of the important phrases and concept for each category. The degree of interdependency was then categorized to prioritize conditioning variables on the basis of its importance for pluvial flood susceptibility assessment. This interdependency process was selected because it describes the relationship between two categories and the correlation with others [13], meaning two categories of conditioning variables are interdependent when each is dependent on the other.

The degree of interdependency index was evaluated by values between 0 and 1 where 0 shows the absence of interdependency and 1 shows the maximum interdependency between the three categories. To rank the interdependency, the scores for each conditioning variable categories were added. The total score for a row reflected the leadership index and the column score was the index of subordination. The categories with the highest leadership index will be given the priority in selecting the conditioning variables for a pluvial flood. Both index scores for each category were then added to provide the ranking.

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The interdependency ranking process was conducted by 15 assessors from academics and the environmental professionals. The assessors were selected to ensure the process was completed by an interdisciplinary team which was chosen based on respected knowledge and peer-reviewed publications. The scores by each assessor were aggregated and averaged to provide a prioritization of pluvial flood conditioning variables.

3. RESULTS

3.1 Literature Search

The search strategy identified 2432 potentially useful articles. After applying the inclusion and exclusion criteria, 106 full-text articles were analysed, out of which, 64 were rejected because they did not include pluvial flood, urban flood, factors, variables and discussing how conditioning variables can be categorised. The remaining 42 were identified as being relevant and data were extracted. (Figure 1)

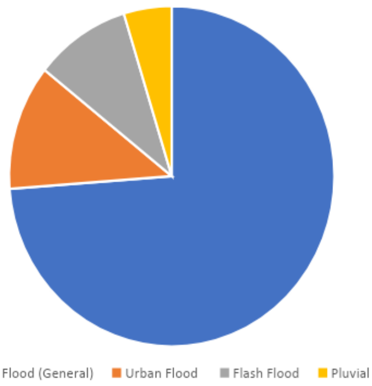
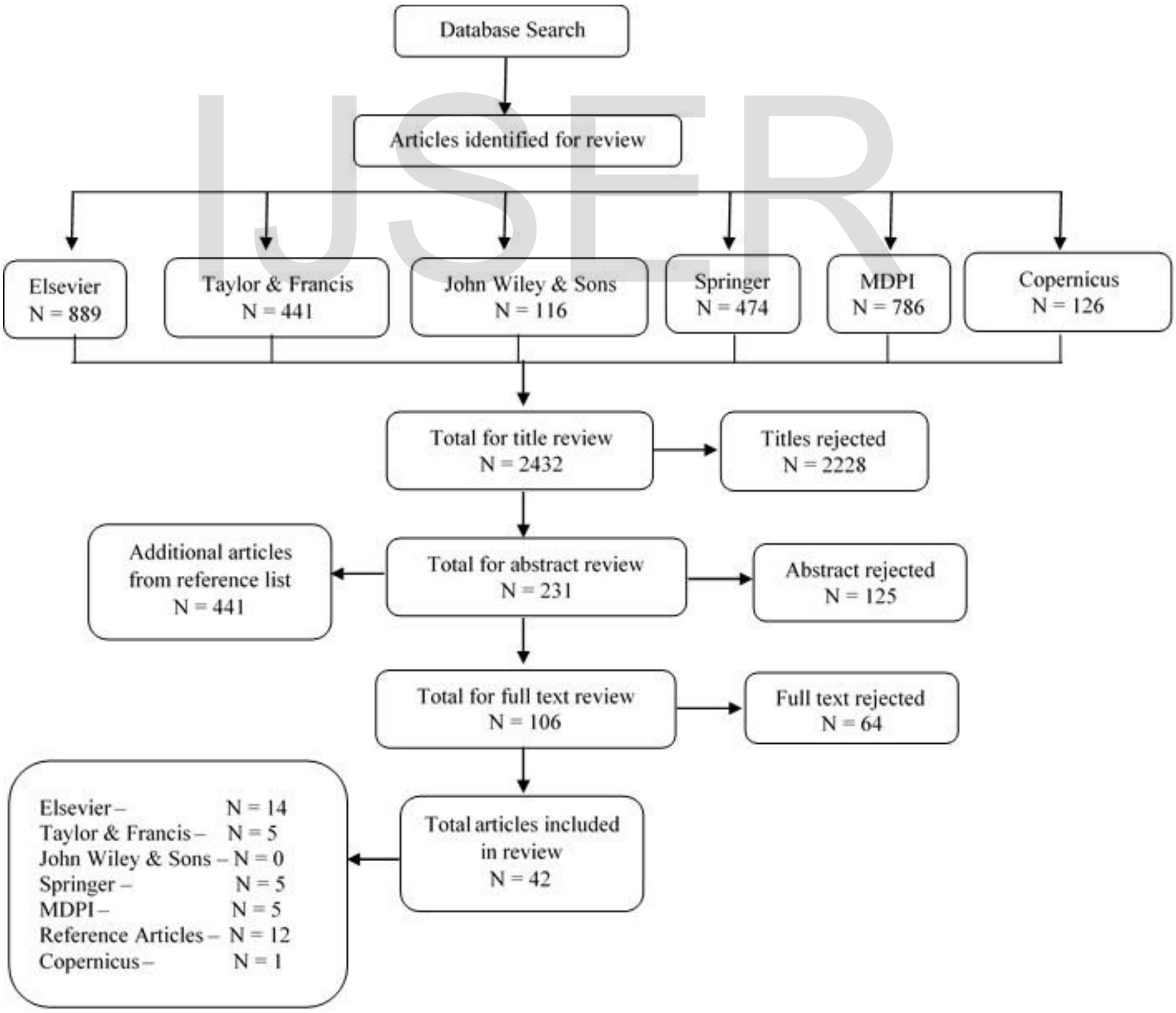


Figure 2: Literatures by flood types

3.2 Data Evaluation

A matrix was developed to provide an individual case description for each article (Table 1). The most common data type was quantitative articles (n = 32, 76.2%) followed by qualitative (n = 5, 11.9%), literature review (n = 2, 4.8%), mixed method (n = 3, 7.1%). Thus 4.8% of the articles were literature review and 95.2% were scientific (mixed, quantitative and qualitative). Of the 42

Figure 1: Literature review graphical description



articles, 31 (73.1%) focused majorly on the flood, 5 on urban type of flood which can be also considered as pluvial flood, 4 on flash type of flood (9.5%) and the remaining 2 (4.8%) on pluvial type of flood (Figure 2). The majority of the articles (n =12, 30.0%) used Nigeria as a case study (Figure 3). The next most used was Iran (n = 7, 17.5%) followed by China (n = 4, 10.0%), Vietnam and Malaysia (n = 3, 7.5%) with South Korea (n = 2, 5.0%). The countries used as a case study in the articles were Kenya, Denmark, Pakistan, Jamaica, Australia, Poland, India, USA and Ethiopia (n = 1).

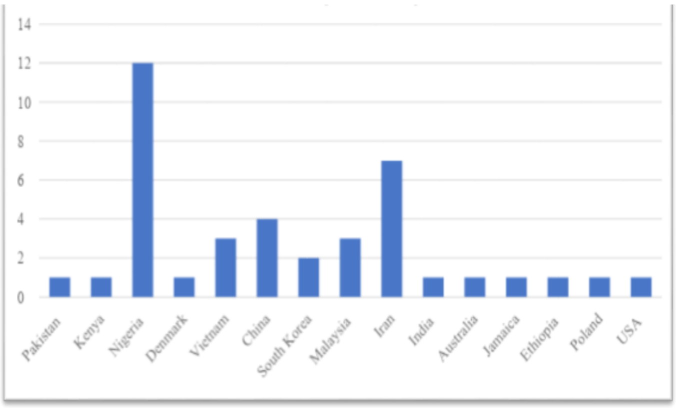


Figure 3: Literatures by case study

Table 1: Individual case study description

Article	Citation	Data Type	Conditioning variables	Case Study	Flood Type	Article Name
F13	[14]	Quantitative	rainfall distribution, elevation and slope, drainage network and density, land-use/land-cover and soil type.	Kenya	Urban Flood	MDPI - Water
F14	[15]	Quantitative	Socio-economic indicators, Susceptibility indicators, Exposure indicators and recovery indicators	Nigeria	Urban Flood	Springer
F20	[16]	Quantitative	temperature and rainfall	Nigeria	Flood	American Journal of Engineering Research
F27	[17]	Quantitative	slope, elevation, curvature, NDVI, stream power index (SPI), topographic wetness index (TWI), lithology, land use, rainfall, stream	Iran	Flood	Elsevier - Environmental Modelling and Software
F29	[18]	Quantitative	(a) Slope angle (degree), (b) Elevation (meter), (c) Curvature (100/meter), (d)NDVI, (e) SPI, (f) TWI, (g) Lithology, (h) Land use, (i) Rainfall (mm), (j) Stream density (m/km2) and (k) Distance to rivers (meter).	Iran	Flood	Elsevier - Science of the Total Environment
F31	[19]	Quantitative	elevation, slope, aspect, curvature, plan curvature, profile curvature, proximity to roads, proximity to streams, proximity to the river and land use/land cover	Pakistan	Flood	International Journal of Environment and Geoinformatics

F37	[20]	Qualitative and Quantitative	spatial data, land use data (rainfall and precipitation)	Denmark	Pluvial Flood	Elsevier - Journal of Hydrology
F40	[2]	Quantitative	land cover, soils, microtopography (LiDAR data), and projected hydro-meteorological conditions, spatial data to estimate the volume of surface, runoff (soil type and its infiltration capacity; land use and land cover; height of predicted precipitation; and topography)	Poland	Pluvial Flood	MDPI - Water
F42	[5]	Qualitative	Rainfall, Precipitation	USA	Pluvial Flash Floods	MDPI - Sensor
F43	[21]	Qualitative	the topography of the area, land use (LU) and land cover (LC) modifications, and influence of canals, lagoons, and beaches	Nigeria	Urban Flood	Nat. Hazards Earth Syst. Sci.,
F46	[22]	Quantitative	elevation, slope, aspect, curvature, toposhade, topographic wetness index, stream power index, stream density, NDVI, soil type, lithology, and rainfall	Vietnam	Flash Flood	Elsevier - Catena
F50	[23]	Quantitative	elevation, slope, aspect, curvature, toposhade, topographic wetness index, stream power index, stream density, NDVI, soil type, lithology, Rainfall, Precipitation	China	Urban Flood	Elsevier - Science of the Total Environment
F52	[24]	Qualitative and Quantitative	Primary and Secondary data	Nigeria	Flood	International Journal of Physical and Human Geography
F53	[25]	Quantitative	C1=drainage density, C2=basin slope, C3=Elevation, C4=Size of micro Watershed, C5=soil, C6=annual rainfall and C7=Land use).	Ethiopia	Flash flood	Journal of Remote Sensing & GIS
F55	[26]	Quantitative	altitude, aspect, slope, curvature, stream power index, topographic wetness index, sediment transport index, topographic roughness index, distance from the river, geology, soil,	Malaysia	Flood	Geomatics, Natural Hazards and Risk

			surface runoff, and land use/cover (LULC)			
F56	[27]	Quantitative	elevation, slope, aspect, curvature, topographic wetness index (TWI), stream power index (SPI), toposhade, stream density, rainfall, normalized difference vegetation index (NDVI), soil type cover and lithology cover	Vietnam	Flash Flood	Elsevier - Science of the Total Environment
F57	[28]	Quantitative	heavy rainfall, blocked and/or failure of drainage systems, and lack of land use planning	Nigeria	Flood	Urban Water Systems & Floods
F58	[29]	Quantitative	Rainfall (Precipitation), Drainage network of the river basin, Slope of the basin, Soil type, Land Cover	Nigeria	Flood	European Journal of Scientific Research
F60	[30]	Quantitative	lithology, land use, distance from rivers, soil texture, slope angle, slope aspect, plan curvature, topographic wetness index (TWI), and altitude	Iran	Flood	Geocarto International
F61	[31]	Quantitative	topography, geology, soil and land-use, degree of slope, stream evolution, soil, vegetation, morphology, land use, lithology, geological structure	Korea	Flood	Geomatics, Natural Hazards and Risk
F62	[32]	Quantitative	topography, geology, soil, and land use.	South Korea	Urban Flood	MDPI – Sustainability
F63	[33]	Quantitative	slope angle, slope aspect, altitude, plan curvature of the terrain, land use, lithology, distance from the river, topographic wetness index, soil type and drainage density	Iran	Flood	Geocarto International
F65	[34]	Quantitative		China	Flood	Elsevier - Journal of Hydrology
F66	[35]	Quantitative	elevation, slope, topographical wetness index, geomorphology, soil type, drainage, rainfall, and LULC (land use/land cover)	India	Flood	Modeling Earth Systems and Environment

F67	[36]	Quantitative	lithology, soil cover, elevation, slope angle, aspect, topographic wetness index (TWI), plan curvature, profile curvature, stream power index (SPI), sediment transport index (STI) and distance from river network,	China	Flood	Elsevier - Science of the Total Environment
F68	[37]	Quantitative	longitude (LO), latitude (LA), elevation (EV), drainage density (DD), average annual maximum daily precipitation (AP), extreme daily precipitation (EP), frequency of heavy rainstorms (FP), soil moisture (SM), curve number (CN), vegetation coverage (VC), slope (SL), and relative elevation (RE).	China	Flood	Elsevier - Science of the Total Environment
F69	[38]	Quantitative	slope degree, plan curvature, altitude, topographic wetness index (TWI), stream power index (SPI), distance from the river, land use/land cover, rainfall, and lithology		Flood	Elsevier - Science of the Total Environment
F73	[39]	Quantitative	soil map, rainfall data and Drainage density	Nigeria	Flood	World Environment
F74	[40]	Quantitative	river centre line, bank lines, flow path, cross-sections	Nigeria	Flood	FUOYE Journal of Engineering and Technology,
F75	[41]	Quantitative	Topographic Map, Geology Map, Land-sat ETM, DEM, Rainfall, Soil Map	Nigeria	Flood	Greener Journal of Environment Management and Public Safety
F80	[42]	Quantitative	Distance from mainstream and river, Elevation, Slope, Land use and land cover, Population density, Distance from discharge channel,	Malaysia	Flood	Research Journal of Applied Sciences, Engineering and Technology
F81	[43]	Quantitative	altitude, slope, aspect, curvature, geology, soil, land use/ cover (LULC), topographic wetness index (TWI), stream power	Australia	Flood	Geomatics, Natural Hazards and Risk

			index (SPI), terrain roughness index (TRI), sediment transport index (STI), and distance from rivers and roads,			
F82	[10]	LR	Review	Nil	Flood	Natural Hazards
F83	[44]	Quantitative	precipitation, slope, curve number, distance to the river, distance to the channel, depth to groundwater, land use, and elevation.	Iran	Flood	Elsevier - Journal of Hydrology
F84	[45]	Qualitative	land cover data, soil type and texture classification, Topographic map, Rainfall data	Nigeria	Flood	Geology, Ecology, and Landscapes
F85	[46]	Qualitative	slope, stream power index (SPI), topographic wetness index (TWI), altitude, curvature, distance from the river, geology, rainfall, land use/cover (LULC), and soil type	Malaysia	Flood	Elsevier - Journal of Hydrology
F87	[47]	Quantitative	slope, elevation, curvature, topographic wetness index (TWI), stream power index (SPI), distance to the river, stream density, NDVI, lithology, rainfall.	Vietnam	Flood	Elsevier - Journal of Hydrology
F88	[48]	LR	(i) Meteorological Parameters, ii. Hydrological Parameters (iii) Socio-Economic Factors (iv) Combination of Hydrometeorological and Socio-Economic Factors.	Nigeria	Flood	J. Appl. Sci. Environ. Mgt.
F96	[49]	Quantitative	(a) Altitude (m), (b) Slope angle (In degrees), (c) plan curvature (100/m), (d) topographic wetness index (TWI), (e) Stream power index (SPI), (f) distance from river (m), (g) rainfall (mm), (h) geology, (i) land use, and (j) NDVI. (Topographic Factors, Water-Related Factors, Physical Factors)	Iran	Flood	MDPI – Remote Sensing
F101	[50]	Quantitative	Microscale environmental variables of land use and landcover typologies, rainfall, NDWI, DEM, slope, geological formation and population density were used as input	Nigeria	Flood	Journal of Environment and Earth Science

F102	[51]	Quantitative	annual rainfall, bedrock geology, soil properties, land use, land elevation, slope angle, slope aspect, flow accumulation, flow direction, the topographic wetness index, and the distance from the nearest river.	Jamaica	Flood	Springer – Environ. Earth Science

3.3 Categorization of Conditioning Variables

There were 56 different descriptions of conditioning variables which were categorised into 3 categories. (Table 2, Figure 2). These included topographical, hydrological and anthropological. Each of the categories had varying descriptions and citations. The category with the highest number of descriptions was topographical (n = 27), followed by anthropological (n = 18) and hydrological (n = 10). The category with the most citation was topographical (n = 33), followed by hydrological (n = 29) and anthropological (n = 27), where n is the number of the identified conditioning variables and literature citations. The spatial distribution of a flood event is dependent on the following factors: local geologic, geographic, geomorphic, climatological, hydrological and anthropogenic. A description of the categories follows (Table 2):

3.3.1 Topographical

The topographical category forms a key intensifying factor in the severity of flooding and in categorizing flood-prone areas. The conditioning variables characterised as topographical factors include (Table 2). Elevation is raised geological formation or distance while Slope is a smooth flat area of ground that tends downwards or upwards. It is the measure of steepness relative to the horizontal plane. They both play an important role in governing the stability of geological formation (terrain). Land use reflects the current use of the land, pattern and type of its use likewise land cover which is known as the physical material at the surface of the earth. Land use and Land cover constitute a further primary factor strongly contributing to flooding and its occurrence. Soil type in any vicinity is very important as they control the amount of water that can infiltrate into the ground, and hence flooding. The structure and infiltration capacity of soils will also have an important impact on the efficiency of the soil to act as a sponge and soak up water.

Aspect this is useful in flood analysis due to the impact on precipitation and sunshine levels. It is defined as the direction of the maximum slope of the surface terrain. Toposhade is related to the convergence and direction of water flowing which correspond to the shade and the length of the hillslopes. Topographic wetness index (TWI) exhibits the amount of water accumulation in a pixel size of the watershed area at a specific location. It is referred to as an index that is capable of predicting areas susceptible to saturated land surfaces and areas that carry the potential to produce overland flow. Curvature is a factor in runoff flow and can be useful for detecting flood susceptibility. Lithology is also a vital factor that is responsible for the Spatio-temporal variation observed on hydrology and sediment production within a watershed.

Geology is a physical factor that plays a significant role in flood susceptibility due to the variable sensitivity of lithological units. Soil cover and depth are considered as the depth of the soil layer from the ground surface to bedrock and the type of soil that levels a specific location. NDVI (normalized difference vegetation index) is a measure which describes the vegetation characteristics of an area, and influences both the surface runoff and infiltration capability of a specific location. Profile curvature is parallel to the direction of the maximum slope affecting the acceleration or deceleration of flow across the surface. Slope, slope angle and aspect control the speed of the surface runoff. The slope angle plays a very important role in the identification of susceptible areas to flood occurrence. Topographic roughness index (TRI) calculates the difference of elevation values from a centre cell and the eight cells immediately surrounding it. It expresses the amount of elevation difference between adjacent cells of a DEM. Soil texture controls the generation of surface runoff and inundation process. The water infiltration primarily depends upon soil texture. Relative elevation (RE) reveals the degree of elevation change within a grid cell.

3.3.2 Hydrological

Stream Power Index represents the power of water flow in terms of erosion affecting surface runoff. It could be used to determine the place where soil conservation measures can decrease the erosive effects of concentrated surface runoff. Rainfall is the quantity of rain falling within a given area in a given time. Rainfall is a form of precipitation which is in the form of water drops of sizes larger than 0.5mm. It is a key influencing factor when it comes to flooding. Vegetation coverage is calculated with the average of monthly normalized difference vegetation index. Temperature is an objective measure of how hot or cold an object is. Stream density which is computed by dividing the length of the river (stream length - m/km) over the basin area (km^2). The regions with higher stream density are more likely to have a rapid response to a rainstorm. The stream density of a watershed has a significant influence on the extent and intensity of flooding. Flow accumulation of a point represents the upslope catchment area from which water may flow.

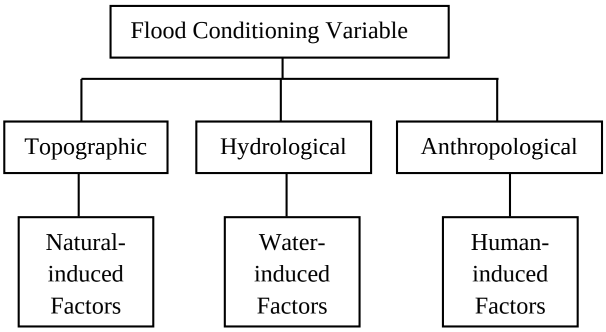
3.3.3 Anthropological

Drainage density is defined as the total stream length per unit area. Poor drainage systems often result in river overflow and continuous flooding. Drainage network is defined as the ratio of the entire length of the canals in the watershed to the areas of the watershed. Flow direction is a grid whose value represents the duration of flow for each cell to its steepest downslope neighbour. Depth to groundwater level, infiltration capacity generally depends on soil moisture and depth to groundwater which directly affects the surface runoff volume during high-intensity precipitation. Surface runoff is when the soil capacity is fully saturated by water throughout the land and the water flow exceeds the required limits. Distance to channels or drainage systems in the urban environment collects surface water, while distances from discharge channels are defined based on the class of discharge channel. Distance from the river has a significant impact on the flood spread and magnitude. Population and Urban density provide information to recognise the area with higher concentration of the population in an area with a higher population density more people and infrastructure are likely to be affected by the flood. It helps to know the number of individuals inhabiting a given urban area.

Table 2: Flood conditioning variables categories and description

Categories	**Description**	**References**
Topographical	elevation, slope, land use, land cover, soil type, topography, aspect, toposhade, topographic wetness index, curvature, lithology, geology, soil cover, normalized difference vegetation index, plan curvature, profile curvature, slope angle, slope aspect, soil p, soil depth, topographic roughness index, soil texture, relative elevation, morphology, geomorphology, longitude, latitude	F13, F27, F29, F31, F35, F37, F40, F43, F46, F50, F53, F55, F56, F58, F60, F61, F62, F63, F65, F66, F67, F68, F69, F75, F80, F81, F83, F84, F85, F87, F96, F101, F102 (See Table 1)
Hydrological	rainfall, precipitation, vegetation coverage, temperature, frequency of heavy rainfall, stream power index, stream density, flow accumulation, stream evolution	F13, F20, F27, F35, F37, F40, F42, F46, F50, F53, F55, F57, F58, F60, F61, F65, F66, F68, F69, F73, F74, F75, F83, F84, F85, F87, F96, F101, F102 (See Table 1)
Anthropological	drainage density, drainage network, population density, failure of the drainage system, distance from rivers, distance from drainage channel, flow direction, proximity to roads, proximity to the river, depth to groundwater, distance from discharge channel, proximity to a stream, size of micro watershed, surface runoff, distance to the channel, urban density, quality of building, age of a building	F13, F27, F29, F31, F43, F46, F50, F56, F57, F58, F61, F63, F65, F66, F67, F68, F69, F73, F74, F75, F80, F81, F83, F87, F96, F101, F102 (See Table 1)

Figure 2: Flood conditioning variables categories



3.4 Data Analysis: Degree of interdependency

Seven (7) assessors conducted an evaluation of each conditioning variable, out of the fifteen (15) assessors that were reached out and averaged the scores.

Hydrological category of the conditioning variables was identified as the most important, it was the highest-ranked on the leadership index (2.5) while the anthropological category had the greatest dependency on other categories (2.2). The next categorization of conditioning variables on the leadership index were topographical (2.2) followed by anthropological (1.6). The next categorization after anthropological with the greatest dependency on others was topographical (2.1) followed by hydrological (2.0). (Table 3).

Table 3: Conditioning Variable Categorization Interdependency Matrix for pluvial flood

Conditioning Variable Categorization	Topographic	Hydrological	Anthropological	Leadership Index
Topographical	1	0.7	0.5	2.2
Hydrological	0.8	1	0.7	2.5
Anthropological	0.3	0.3	1	1.6
Subordination Index	2.1	2.0	2.2	

An aggregation of the leadership and subordination index scores provided a ranking for categorization of conditioning variables. (Table 4). On this basis, the following categorization priorities were identified: 1, hydrological, 2. topographical and 3. anthropological.

Table 4: Ranking and categorization of conditioning variable categories in pluvial flood

Conditioning Variable Categories	Leadership Index (Ranking)	Subordination Index (Ranking)	Combined Score
Hydrological	2.5 (1)	2.0 (3)	4.5
Topographical	2.2 (2)	2.1 (2)	4.3
Anthropological	1.6 (3)	2.2 (1)	3.8

3.5 Discussion

Hydrological category of the conditioning variable can be considered the most important of the three categorizations as related to pluvial flooding. Pluvial flooding can broadly be defined as flooding that results from rainfall, generated overflow and ponding before the runoff enters and watercourse, drainage system or sewer or cannot enter it because the network is full to capacity. The hydrological conditioning variables involve rainfall, precipitation, vegetation coverage, temperature, frequency of heavy rainfall, stream power index.

Flooding can be caused by different factors, the findings support the study by [52], that factors such as drainage systems capacity, land use will determine whether a severe rainfall event will cause pluvial flooding and for any form of pluvial flood mitigation approach to operating, identifying the rainfall condition likely to cause pluvial flooding at a particular location is highly relevant. Also, by [3], that pluvial floods in Pattani region come from heavy rain. The report by [53] highlighted climate change population growth, drainage capacity coming together to produce pluvial flooding, also [21] listed climate change, poor urban planning, urbanization and anthropogenic activities such as drainage construction, blockage of drainage facilities, failure of flood warning, violation of building regulation and dumping of refuse into drainage are the main causes of pluvial flooding.

[2] highlighted soil type, land use and cover, precipitation and topography as spatial data input for pluvial flood risk assessment. [3] also describes how climate change effects, urbanization, soil characteristics, land cover and use serves as a number of factors that affect the intensity of pluvial floods. [5] explained that pluvial floods are not simply caused by weather phenomena. They depend not only on the amount and duration of precipitation but also on the hydrological characteristics of the basin such as runoff magnitude, antecedent moisture condition, drainage area, soil type and land. [54] identified poor drainage capacity, unplanned urban development and the biggest factor

rainfall as part of the human-induced factors that cause two-third of flooding in Nigeria. The aforementioned and identified factors are attached to pluvial flooding from previous studies and are mainly under the classified hydrological and topographical according to the findings of the study. The findings of this study support an earlier study by [37], dividing the conditioning variables into three based on the mechanism of pluvial flooding namely precipitation factors, topographical factors and anthropogenic factors. Also support the study by [36], which identified the conditioning variables as geographical, meteorological and hydrological factors.

4. Conclusion

The hydrological category of the conditioning variable categorization was identified as the most important of the three (3) categories related to pluvial flood. If those conditioning variables in the category do not exist, it has the greatest impact on the occurrence of pluvial flood and are highly dependent on the other categories. The next category is topographical followed by anthropological. Overall, the findings presented are a step towards providing a framework or guidelines in the selection of pluvial flood conditioning variables. This finding is a step toward providing a clear defined category to effectively inform the preparation for the development of the pluvial susceptibility map using machine learning techniques. Teasing out pluvial flooding from articles was difficult in some instances as some activities could include surface water (flash) flooding or other flooding type, despite this limitation, the three main categories were clearly an evidence, all of which should be subjects of continued research and development in the future.

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