Geospatial Mapping of Inland Flood Susceptibility Based on Multi-Criteria Analysis – A Case Study in the Final Flow of Busu River Basin, Papua New Guinea

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Abstract
Floods are one of the most extensively dispersed risks all over the world. The aim of this research is to map out potential flood susceptible zones and analyse the risk using integrated Remote Sensing (RS) and Geographic Information System (GIS) Technology. RS techniques present inexpensive and quicker decisions for retrieving spatial data about the flood occurrence in the actually unreachable areas. On the other hand, GIS techniques enable hydrological demonstrations in data gathering, examination, querying, and demonstration of information in a further easy layout. This research focused on the flooding problem in the Busu River basin and demonstrated a detailed geospatial mapping of inland flood susceptibility based on Multi-Criteria Analysis (MCA) approaches like Pairwise comparison, ranking and weight, and Boolean logic. Different flood factors namely slope, elevation, flow accumulation, soil drainage, soil texture, surface runoff, distance to the active channel, land use land cover, and lithological characteristics were considered for the flood hazard assessment in the lower catchment of the Busu River. Storm rainfall data were used to calculate surface runoff, while the population layer was used for flood vulnerability analysis by overlaying them on the flood hazard map. These flood susceptibility maps especially from Pairwise comparison and ranking approaches can be used for flood mitigation and flood hazard preparedness, as they are more accurate than the Boolean logic approach.

Keywords: Flood, Geographic Information System, Multi-Criteria Decision Analysis, Remote Sensing, Risk assessment

1. Introduction

Floods cause damage to natural resources and the quality of the environment and indirectly contribute to increasing poverty, which consequently increases the vulnerability of both natural and human systems [1]. The effect and rates of natural disasters are on the rise each year. More than 18% of all-natural disasters occur in developing countries and 50% to 60% of these countries are extremely vulnerable [2]. Flood remains highly a customary natural disaster and the size and the economical approach to flood disasters are at their peak in the affected area around the world. The terms "floods", "flood hazard", and "flood risk" cover a broad range of phenomena. The terms such as "flood risk" and "flood losses" are essentially our interpretation of the negative economic losses and social consequences of natural events. Flood risk may increase due to human activity and may decrease through appropriate flood management and planning [3].

Flood is a general temporary condition of partial or complete inundation of normally dry areas from overflow of inland or tidal waters or from unusual and rapid accumulation or runoff [4]. Floods are a natural phenomenon that results in temporary submerging with water and destructs agricultural lands, built environment, and infrastructure and may result in casualty, loss of lives, and economic loss [5] [6] [7] [8] [9] [10] and [11]. Flood does not occur under normal conditions and cannot be prevented causing displacement of people [12]. Floods pose a threat to environmental and socio-economic effects [13] [14] [15] and [16]. A number of factors trigger inland flooding.

Heavy precipitation is a major contributing factor to flood disasters when the normal waterway cannot transport the extra water from the rain due to the unavailability of a proper drainage network [17]. Nonetheless, heavy rainfall is not the only factor to flood disasters; floods can also be triggered by dam failures, tsunamis, storm surges, etc. that may have resulted from geological activities. Floods may occur due to anthropogenic activities and human interventions in the natural processes such as the increase in settlement areas, population growth, and economic assets over low-lying plains prone to flooding leading to alterations in the natural drainage and river basin patterns, deforestation, and climate change [18].

Lae, the second largest city of Papua New Guinea had experienced two major flood and mudslide disasters. In both cases, hundreds of people lost their homes. The 1983 floods remain the worst since the establishment of the town in the late 1920s. These floods left hundreds of people homeless particularly those living along the banks of the Bumbu River [18]. Many houses were damaged and hundreds of people at the Five Mile settlement along the Highlands Highway were affected by mudslides. The Busu River in the Naweb District of Morobe Province is one of the most flood-problematic rivers. The basin is classified as one of the most devastating flooding rivers in Papua New Guinea. Reviewing the past records and oral histories of the Busu River, the area near the basin encountered a lot of flood occurrences which led to the loss of lives and properties [18]. Today Busu River is still a threat to the people living around and near the river. This is endorsed by the climate changes and other major flood factors that made adjustments in sedimentation weight and water capacity. The river flows wide due to the flatness of the landforms in the floodplain zone. These are the consequences of the flooding of the extremely huge region and there are many additional channels established which do not connect to the major channel. The rivers geomorphology changes due to the additional streams, which presents a clear understanding about the river and causes of flooding. The geomorphic, hydrological, and topographic features along the river with other persuasive factors aid in the flood hazard examination for Busu River that revealed information for governmental departments, planners, settlers, and other benefactors to make better decisions that will minimize the flood damages in terms of properties, farms, and even lives. It is important to create flood hazard maps that are user-friendly that will help focus on the mitigation validities.

Many methods were used to study flood issues by different workers around the world with their own sets of parameters according to individual river situations. This flood assessment and flood risk mapping approach include geomorphology, hydrology, topography, demography, and meteorology as subsidiary parameters [19]. RS and GIS technology has become suitable platform that has the capability to deliver large bulks of information on a well-timed basis and cost-effectively. Till now, a lot of recognized achievements have been encountered with the use of satellite data and geomorphology in flood risk assessment and mapping. Compound analyses, like flood susceptibility evaluation and flood loss evaluation, are still active issues to work on.

The GIS-based models with varying numbers and types of flood-influencing factors have been successfully utilized in the mapping of inland flood hazard areas by several studies [19] [20] [21] [22] [23] [24] [25] [26] [27] [28] and [29]. In the recent past, different geospatial methods were used in flood analyses, which have proven themselves much more effective and realistic. Hydrological models are the first category which includes SWAT [29], WetSpa and HYDROTEL [30], and hydrodynamic approaches based on the shallow water equations initialized by rainfall [31] [32] and [33]. Statistical and knowledge-based methods were also proven to be much more effective in flood analysis, which includes weights of evidence (WoE) [29] [34] and [35], logistic regression (LR) [35] [36] and [37], analytic hierarchy process (AHP) [38] [39] [40] and [41], frequency ratios (FR) [28] [42] and [43]. Machine learning models can handle complex nonlinear problems such as neuro-fuzzy logic [44], artificial neural networks (ANNs) [45] and [46], decision trees (DTs) [47], support vector machines (SVMs) [48] and [49], adaptive neuro-fuzzy inference system (ANFIS) [50], biogeography based optimization and BAT algorithms [51], reduced error pruning trees [50], multivariate adaptive regression splines [52]. Multi-Criteria Decision Analysis (MCDA) approach can employ the combination of socioeconomic, environmental, and technical objectives to achieve the most favorable decision [19] and [53] and has proven to be the best model in flood analysis [54] and [55].

The study aims to focus on flood susceptibility mapping using various spatial models like Pairwise comparison, ranking, and Boolean logic. The core assignment of this research is to the identification of flood hazard zones in the lower catchment area of the Busu River. Three objectives were considered to achieve the aim of this study.

First objective was to identification and preparation database on different input parameters for flood susceptibility mapping in the lower catchment area of Busu catchment. Secondly, to develop potential flood risk zones through multi-criteria decision approaches and establishes the best method after the validation process. Finally, to perform flood vulnerability assessment after overlaying flood risk zone database and population information and other infrastructure.

2. Study Area

Busu River is considered one of the fast-flowing rivers in Morobe Province and is located just outside of Lae City, the capital of Morobe Province. Busu River is made up of all the tributaries in the Sankwep catchment (Figure 1). Sankwep is one of the many catchments in Morobe Province. Sankwep catchment mostly takes up Nawae and Lae Districts with the lower portion of the Kabwum district. This study only concentrates on the Busu flood plain zone. This area is situated in the Ahi Local Level Government in Lae District, situated between the longitudes of 147º03′00″ E and 147º01′12″ E and the latitudes of 06º39′52″ S to 06º43′30″ S. Morobe is one of the provinces with well-known rivers with Markham the largest river with Busu the fast-flowing river. Busu originated from the Gain, Boana, Lambaip, and Kwapsanek mountain ranges and it is named based on the famous Busu Mountain, which is the main tributary. Along with its tributaries, the river drains a large amount of area in Morobe Province, particularly in the Naweb and Lae Districts. Mountains and ridges in the source zone bound Busu River to flow faster and it is the fastest flow in the country. The river is merged by main tributaries in Kwapsanek range north of the Revival Centers of Papua New Guinea Headquarters, the other major tributaries joined from the Gain, Boana, and Kwalan areas, which are east of the Nazab Airport.

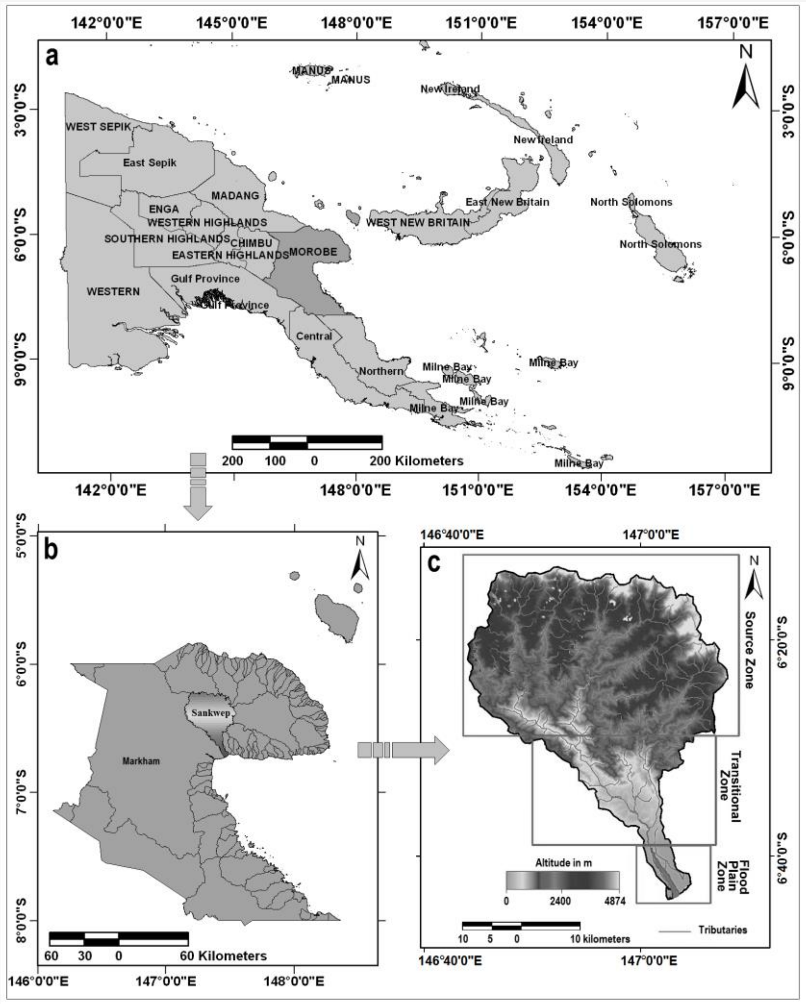

Figure 1: Location map of the study area: (a) Papua New Guinea, (b) Morobe province and (c) Longitudinal structure of the Sankwep catchment

The river has built a mega-fan of some 25,000 square kilometers in extent breaking into two districts, mostly the Naweb District, all with changing passages due to the flooding. The Sankwep, Busip, and Gobadik are the major tributaries of the Busu River with other minor tributaries. The watercourse often changes the path and affects the local settlement [56]. This shift of the channel happens due to the flood, which is repetitive because of rainy weather all year round. The flood related damages caused by the Busu River have extreme effects on the people and the environment in the flood-prone areas. The longitudinal structure of the Sankwep catchment showed the source, transitional, and flood plan zone, where the flood plain zone is taken into account for flood susceptibility analysis using different GIS models (Figure 1). The sediments carried during flood return to the old channel (paleo) which causes the river stream to divert in a different direction each year. The main settlements and villages that are assembled near the flood-challenging river are Bumeng, Malanhang, Bumayong, Situm, and other smaller settlements. Settlements that are often affected by the floods were Second Seven, Pepsi, Nabak, and Wain-Busu.

Several attempts have been made to avoid forthcoming river penetration and flooding with local flood protection systems like the establishment of ridges, planting of the bamboo plant, and digging up to redirect the breaching flows to its main canal. Their previous protection schemes failed several times which steered them into great fear, according to the locals living along the river catchment. They feared that the course of the river near its main current will run to the flooding of the settlement if the height of the water increased. Although several works are done previously that considered mitigation measures, it is still uncertain, natural disasters are inevitable. Therefore, it is essential to reflect on the vulnerability and do risk assessments by analyzing the parameters that contributed to the inundations and do better validations upon the results produced using GIS and RS techniques. The Morobe provincial government and the Naweb and Lae Districts local government have raised this concern of risk assessments to do flood mitigations but not to the extent where they can fully mitigate the flood.

3. Methodology

The Busu River flood risk assessment and flood risk zonation database were developed after integrating all thematic layers (controlling factors) which are mandatory in flood susceptibility mapping. Data analysis was done in ArcGIS 10.5 with the use of the DEM to generate the slope map, elevation map and flow accumulation map, and other hydrological analyses. All the data obtained from several resource centers and organizations were converted to the grid or GIS-compatible format for the Busu flood assessment. All the data sets were combined through a multi-criteria analysis approach for the planning of inundation exposure and flood susceptibility map.

3.1 Data used and their Description

Satellite images, topographic maps, rainfall data, population data, digital elevation model (DEM), and historical flood inventory database were used to derive all mandatory input factors for flood susceptibility mapping. Some of these decisive factors include geomorphic features, elevation, slope, land use/land cover, drainage density, flow accumulation, flow direction, rainfall, soil texture, and soil drainage. The usable data with their descriptions for this study are listed in Table 1. Elevation data is essential in any flood risk assessment within a designated drainage basin and Busu is not an exception. Elevation layers explain elevation values from corner to corner of the extent of maps depicting the real world.

Table 1: Data sets and input parameters for flood susceptibility modeling

Type of Data			
Data	**Output Layer**	**Resolution**	**Source**
Lidar Image (Orthophoto)	Land Use layer	20 cm	PNG University of Technology, Surveying and Land Studies Department
Digital Elevation Model	Elevation, Slope, Flow Accumulation	30 m	
Rainfall	Strom Rainfall, Total rainfall	Stationed data 250 m	PNG Resource Information System [57]
Soil	Texture, Drainage	250 m	The PNG Geobook [58]
Geology	Lithological description	500 m	
Flood	Flood points	Point Location	Field Survey using hand held GPS and other historical flood inventory
Population	Population Density	5 people per house	National Population and Housing Census of Papua New Guinea, 2011.

Many other researchers discovered that good elevation data must be included in any analysis relating to elevation to generate improved outcomes with minimal inaccuracy, which have a great ability to implement. The advanced space-borne thermal emission and reflection radiometer (ASTER) DEM is one of the topographic data sets (spatial resolution of 30m) used as the input raster. For regional or local assessments, the 30m ASTER DEM is available for the required topographic information to project potential impacts on the flooding area. The elevation, slope, and flow accumulation layers were generated from the 30m ASTER DEM. Elevations layers are also helpful in 3D visualization in terms of creating watershed delineation. Slopes have greater impacts on hydrology studies. Slope decides whether water is concentrated or isolated [59]. The slope tools under surface analysis of spatial analyst tool bar helps to develop the slope in degree through the simple logic 'the inverse-tangent of the rise divided by the run' from DEM data. The water runs faster when the river source zone has a steep and lengthy slope. In this case, the catchment has a bigger or higher chance of erosion, which leads to flooding in the floodplain zone. The length and the steepness of the slope also affected the flooding of the Busu River [60]. The lowland area with low slope approach floods first as contrasted to the high slope area throughout flood inundation. The regions of the sheer slope indicate excessive topmost flux contrasting to the low-lying region and trigger storage reduction throughout the upper catchments. Flow direction is the direction in which the stream water flows from one pixel to its neighboring pixels and gradually accumulated into each down slope cell called Flow accumulation. Both parameters are very essential for flood modeling [61]. Flow accumulation layer was generated through the navigation of 'Spatial Analyst Tools' followed by 'Hydrology' and 'Flow Accumulation tool'. Before flow accumulation analysis, flow direction layer was prepared using DEM by the fill method. Rainfall is a major factor in flood and flood-related disasters [62]. Local water accumulation and river overflowing are the core sources of flood-associated catastrophes. Lae is known as 'Rainy-Lae' because of unpredictable and heavy rainfall in this area all year round. The continuous heavy downpour has a higher chance of flood. Rainfall data is necessary for considering the water depth in a flood risk assessment. Rainfall has a major impact on the depth of water. Soil type also stimulates rainfall when it reaches the ground. Impermeable soils and rocks such as clay restrict water to infiltrate and increase the chances of long-term water logging and flooding. Therefore, soil data is another important factor to consider in flood assessment [63]. Two separate layers were extracted from the soil data. These layers are soil texture and soil drainage layers. Soil texture describes the amount of sand, silt, and clay-sized units that compose the soil mineral portion. They are classified as loam, sandy loam, or clay. Soil drainage is a regular practice in which water shifts past, within, and away from the soil which results from the gravitational force. Surface runoff is one parameter to understand the flood in any area that is generally derived using the storm rainfall, soil, and land use/land cover based on the Soil Conservation Service (SCS) model. The population is another significant factor in flood risk assessment [43]. Population data enable the authors to calculate the magnitude of the populace exposed to the flood hazard. Better risk assessment is done when accurate and updated data is available. The population data were collected by field survey and interview. The population data was used for vulnerability assessment only.

3.2 Multi Criteria Analysis

Multi-criteria analysis was practiced with the contributing factors of a flood occurrence. The susceptibility areas were demarcated by numerically overlaying all the flood factor layers. Based on the expert's opinions and the availability of data the criteria were selected, compared, and ranked. Three methods were used in this study to identify the inland flood susceptibility zone. These three methods are (i) the Pairwise comparison method, (ii) the Ranking method, and (iii) the Boolean logic method. Furthermore, the resulted outputs were compared to identify the best method after the verification and validation of each using historical flood occurrences (Figure 2).

The Pairwise comparison method was introduced in 1980 [64] to determine the weight of every criterion. This method is the popular method being used by researchers successively [38] [39] [40] and [41]. This method can convert subjective assessments of relative importance into a linear set of weights. This method involves the comparison of the criteria and allows the comparison of two criteria at a time. The values obtained from the weighting of the criteria are entered into the pair-wise comparison matrix. The values in the Pairwise comparison entirely depend on the author's knowledge based on the understanding of the flood factors, the flood history, and the flood characteristics in the study area. Table 2 is filled by comparing one flood factor with another until all factors are compared to each other.

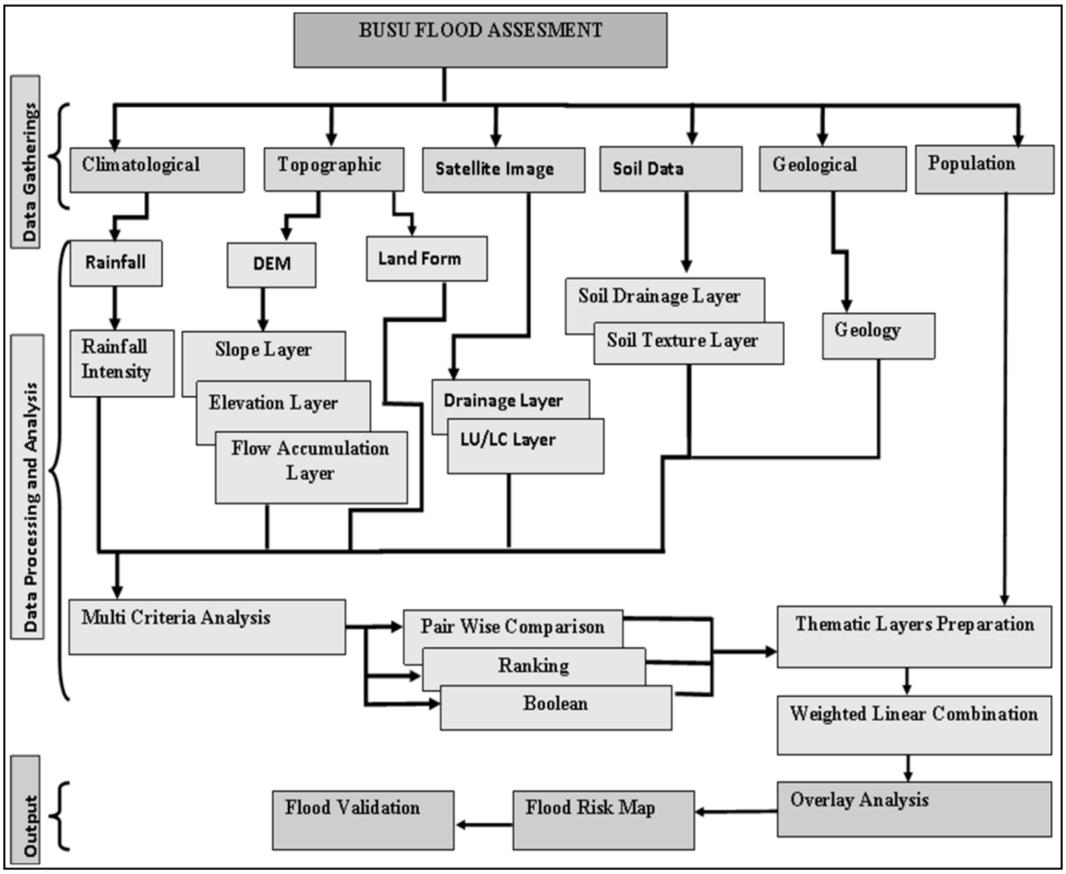

Figure 2: The overall methodological flowchart for inland flood susceptibility mapping

Table 2: Pairwise comparison matrix of the flood factors

Flood Factors	SR	DAC	EL	SL	LULC	FA	ST	SD	LIT
SR	1	2	3	3	5	6	7	9	9
DAC	0.5	1	2	2	3	5	7	8	9
EL	0.33	0.5	1	2	3	5	4	5	6
SL	0.33	0.5	0.5	1	4	6	5	5	7
LULC	0.2	0.33	0.33	0.25	1	7	5	4	6
FA	0.17	0.2	0.2	0.17	0.14	1	3	2	5
ST	0.14	0.14	0.25	0.2	0.2	0.33	1	2	4
SD	0.11	0.125	0.2	0.2	0.25	0.5	0.5	1	3
LIT	0.11	0.11	0.17	0.14	0.17	0.2	0.25	0.33	1
SUM	2.89	4.905	7.65	8.96	16.76	31.03	32.75	36.33	50.00

These factors are shown in the table with their short form, namely Surface runoff (SR), elevation in meters (EL), distance to active channel (DAC), slope in degree (SL), land use/ land cover (LULC), flow accumulation (FA), soil texture (ST), soil drainage (SD), and lithology (LIT).

After the Pairwise comparison matrix is filled, the criteria are normalized to obtain the normalized matrix. The normalized values were obtained by dividing the value in each column by the sum in each column (Table 3). The priority vector is calculated by dividing the row total of the flood factor by the number of flood factors (Table 4). For example, the priority vector of Surface Runoff is 2.59/9 = 0.29. In the next step, lambda (λ) values of each criterion were calculated by multiplying the Priority Vector (PV) with the criteria sum. The λ_{max} ($Lamda_{max}$) was calculated as 10.299. The Consistency Index (CI) was calculated as 0.162 with the help of $lamda_{max}$. The consistency analysis was done through consistency ratio (CR) calculations to check whether the weights are accepted or not and it was recommended that CR should be definitely below 0.2 [65].

Table 3: Normalizing the criteria column to obtain the normalized matrix

Flood Factors	SR	DAC	EL	SL	LULC	FA	ST	SD	LIT	Row Total
SR	0.34	0.4	0.39	0.33	0.3	0.19	0.21	0.25	0.18	2.59
DAC	0.17	0.2	0.26	0.22	0.18	0.16	0.21	0.22	0.18	1.8
EL	0.11	0.1	0.13	0.22	0.18	0.16	0.12	0.14	0.12	1.28
SL	0.11	0.1	0.07	0.11	0.24	0.19	0.15	0.14	0.14	1.25
LULC	0.06	0.07	0.04	0.03	0.06	0.23	0.15	0.11	0.12	0.867
FA	0.05	0.04	0.03	0.02	0.008	0.03	0.09	0.06	0.1	0.428
ST	0.05	0.03	0.03	0.02	0.01	0.01	0.03	0.06	0.08	0.32
SD	0.04	0.03	0.03	0.02	0.01	0.02	0.02	0.03	0.06	0.26
LIT	0.04	0.02	0.02	0.02	0.01	0.006	0.008	0.009	0.02	0.153
SUM	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	

Table 4: Priority vector and weighted percentage

Flood Factors	Row Total	Priority Vector (PV)
SR	2.59	0.288
DAC	1.8	0.200
EL	1.28	0.142
SL	1.25	0.139
LULC	0.867	0.096
FA	0.428	0.048
ST	0.32	0.036
SD	0.26	0.029
LIT	0.153	0.017

In case the number of parameters exceeds 7; the consistency can be expected to be poor [64]. In this research, the CR value was calculated as 0.11 with the help of ratio index (RI) value of 1.46 for nine parameters. Although the CR value is marginally higher, logically it was considered as the acceptable consistency with the use higher numbers of (nine) parameters.

The ranking method is one of the most comfortable operative assessment techniques [66]. In the Ranking Method, multiple conflicting factors are ranked with various importance. The factor ranking of the flood conditioning factors was selected based on the author's preferences and interviewing with the respective local experts. The ranking method is used in a matter where every criterion under consideration was ranked in the order of the decision maker's preference. Each factor is rated according to the estimated significance of causing flooding and ranked using the inverse ranking method [19]. For example, the least influential criterion is ranked 1, then 2 for the next least. Weights in numbers were generated in order to do the criteria ranking [62] and [63]. The criterion values generated for each factor, every factor was weighted according to the predictable implication for flood triggering (Table 5).

A Boolean logic method is an overlay method, where logical operators combine all the criteria [68]. Boolean method is a helpful and commonly practiced analysis operator in GIS [68]. Boolean logic centered on fundamentals of binary logical operations, and its mathematical structures only centered on the values 1 for true and 0 for false. GIS Boolean operators for criteria selections are AND, OR, XOR, and NOT. Most GIS codes Boolean operations precisely are compatible with existing functions and have the same name. Intersect (AND), Union (OR), and Erase (NOT) are familiar operators in GIS. Boolean logic operates in the sense that one searches for areas that come across specific conditions. When the condition is specified or met, it is given the value 1 and when it is not, given zero (0). In the Boolean method, all the nine layers (flood factors) were reclassified in order to convert to integer values of 0, 3, 4 and 5. The non-zero values represent the areas of moderate risk (3), high risk (4) and very high risk (5) respectively and on the other hand, the very low risk and low risk were converted to zero (0). The Boolean AND operations were used to analyse four paired flood factors except surface runoff. The pair factors were (i) Elevation & Slope, (ii) LULC & Distance to active channel, (iii) Soil texture & Soil drainage, and finally (iv) Flow accumulation & Lithology. In the final step, these four pair of intermediate resulted factors and surface runoff factor (five layers) were summed in the raster calculator under spatial analyst tool in ArcGIS10.5 to generate the flood risk map (Figure 3).

Table 5: Rank and weighted of flood factors for the ranking method

Flood factors	**Class**	**Rank**	**Risk vulnerability**	**weighted**
Surface runoff (in mm)	0-25 25-106 106-157 157-189 187-229	1 2 3 4 5	Very Low risk Low Risk Moderate Risk High Risk Very High Risk	9
Distance to active channel (in meter)	Less than 200 200-400 400-600 600-800 More then 800	5 4 3 2 1	Very High Risk High Risk Moderate Risk Low risk Very Low Risk	8
Elevation in meters (in meter)	Less than 15.6 15.7 – 31.8 31.9 – 47.5 47.6 - 65.5 More than 65.6	5 4 3 2 1	Very High Risk High Risk Moderate Risk Low risk Very Low Risk	7
Slope (in Degree)	Less than 3 3-7 7-15 15-30 More than 30	5 4 3 2 1	Very High Risk High Risk Moderate Risk Low risk Very Low Risk	6
LULC	Active Channel Flood Plain Mix Vegetation Agricultural Land Barren Land Settlement Road Sea	5 5 4 4 3 2 1 0	Very High Risk Very High Risk High Risk High Risk Moderate Risk Moderate Risk Low Risk	5
Flow accumulation (Value)	Less than 51 51-102 102-153 153-204 More than 204	5 4 3 2 1	Very High Risk High Risk Moderate Risk Low risk Very Low Risk	4
Soil texture	Silty Clay Loam Sandy Loam Sandy	5 2 1	Very High Risk Low Risk Very Low Risk	3
Soil drainage	Well Drained Moderately Well Drained Poorly Drained	5 3 1	Very High Risk Moderate Risk Very Low Risk	2
Lithology	Alluvial Deposits	3	Moderate Risk	1

4. Results and Discussions

Database on nine different flood contributing factors, namely surface runoff, distance to the active channel, elevation, slope, land use/land cover, flow accumulation, soil texture, soil drainage, and lithology were selected based on the nature of the flood in the study area. These data sets were derived with the help of a digital elevation model, satellite image, rainfall, geology, Geobook, and PNGRIS GIS database of Papua New Guinea. ArcMap 10.5 was used to create these maps with the help of geographic data. Finally, a vulnerability assessment was performed with the help of local infrastructure and population distribution data sets, which were derived from the high-resolution LiDAR data sets of the area. The altitude database was prepared to utilize the 30m ASTER DEM data of the area. The maximum elevation is 93 meters above sea level observed in the northern part of the study area and the minimum altitude of 0 meters (close to the mean sea level) which is very prone to flood, found in the southern part of the basin where the Busu River empty into the Huon Golf (Figure 4a).

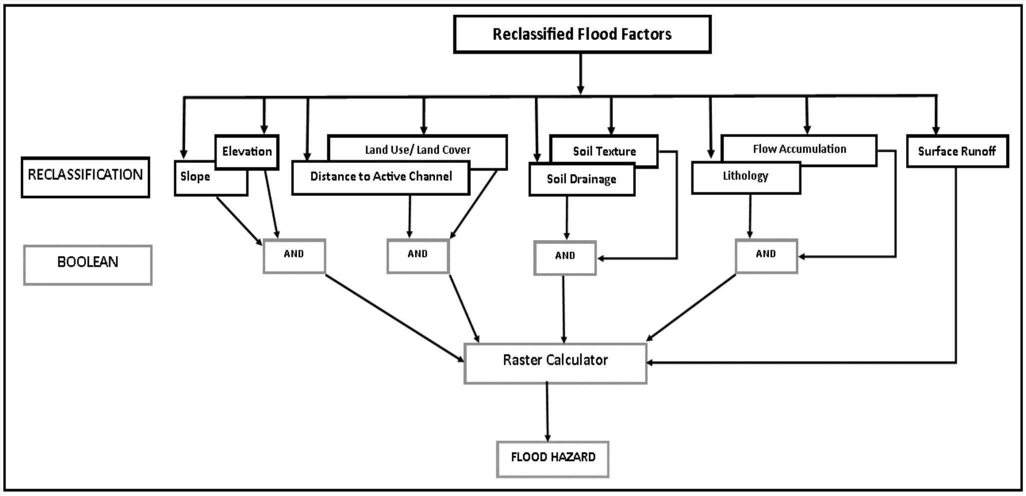

Figure 3: Methodological flowchart of Boolean logic for flood modeling

A flat slope, 0 to 3 degrees is identified in the middle part and the final section of the Busu catchment, which is demarked as a floodplain area. The maximum slope, more than 30 degrees is mapped in the northern part of the study area (Figure 4b). Rainfall is one of the major factors triggering surface runoff, which steers flood disasters in Papua New Guinea. As soon as rain strikes steeped ground it starts to stream overland downward. The surface runoff supplements the maximum amount of water in the river. A watershed is defined as a land area that generates runoff draining to a joint point. Based on the SCS model and curve number (CN) can estimate the surface runoff as a function of storm rainfall, hydrological soil group, and land use/land cover [69]. A three days (21/10/2012 to 23/10/2012) storm rainfall of 229.6 mm was considered as the input for surface runoff calculation. The SCS model derived a mean surface runoff of 191.59mm in the study area (Figure 4c). Supervised Classification was done with ERDAS Imagine 8.5 with the use of the high-resolution LiDAR satellite image to extract land use land cover characteristics of the study area. Through this classification, eight (8) different land use/land cover classes were extracted in the study area. These classes are active water channels, sea areas, mix-vegetation, agricultural land, floodplain, road, barren land, and settlement areas (Figure 4d). The lithological characteristics are an essential criterion for flood vulnerability assessment because it intensifies or makes less the degree of flood outcomes. Rocks with higher permeability coefficient devise minute resistance to water which permits excessive infiltration velocity and the rocks with lower permeability devise a greater resistance to water, which permits a smaller infiltration velocity. Only alluvial deposit is found in the study area (Figure 4e). The distance to the active channel was computed using the Euclidean distance method by 200 meters equally on each bank of the current channel with the help of spatial analyst tools in ArcMap10.5. After the distance to active channel analysis with Euclidean distance, the values were distributed into five classes concerning risk calculation (Figure 4f).

The rate and amount of water traveled through the soil are taken into consideration since they control the water movement. Soil textures, for example, loam, sandy loam, and clay made up the ratio of sand, silt, and clay number of particles that contribute to the mineral portion of the soil. Sand does not grasp much water while clay soils grasp much water. Textures do changes corresponding to the depth and there are three categories of this soil textures; uniform (same texture all through), texture contrast (sudden change in texture), and gradational (textures increase down the soil profile). In the determination of the soil textures, GIS and RS technologies come to aid with the spatial analysis, and the soil texture layer was used for the flood risk assessment. There are three soil textures identified in the study area. They are silty clay loam, sandy loam, and sand (Figure 4g). The three-soil texture falls under two major hydrological soil group (HSG). The sandy loam and sand fall under Group-A, and the silty clay loam under Group D. The soils within Group-A have a lower capacity for runoff, water passes freely by the soil, and the infiltration rate is greater than 0.3 inches/hr when wet. Group-A has less soil and more sand. Group D has a high capacity for runoff; the movements in water through the soils are much more constrained. The Group-D soils have more clay with sand associated and have clayey textures with a lower infiltration rate of 0 to 0.05 inches/hr.

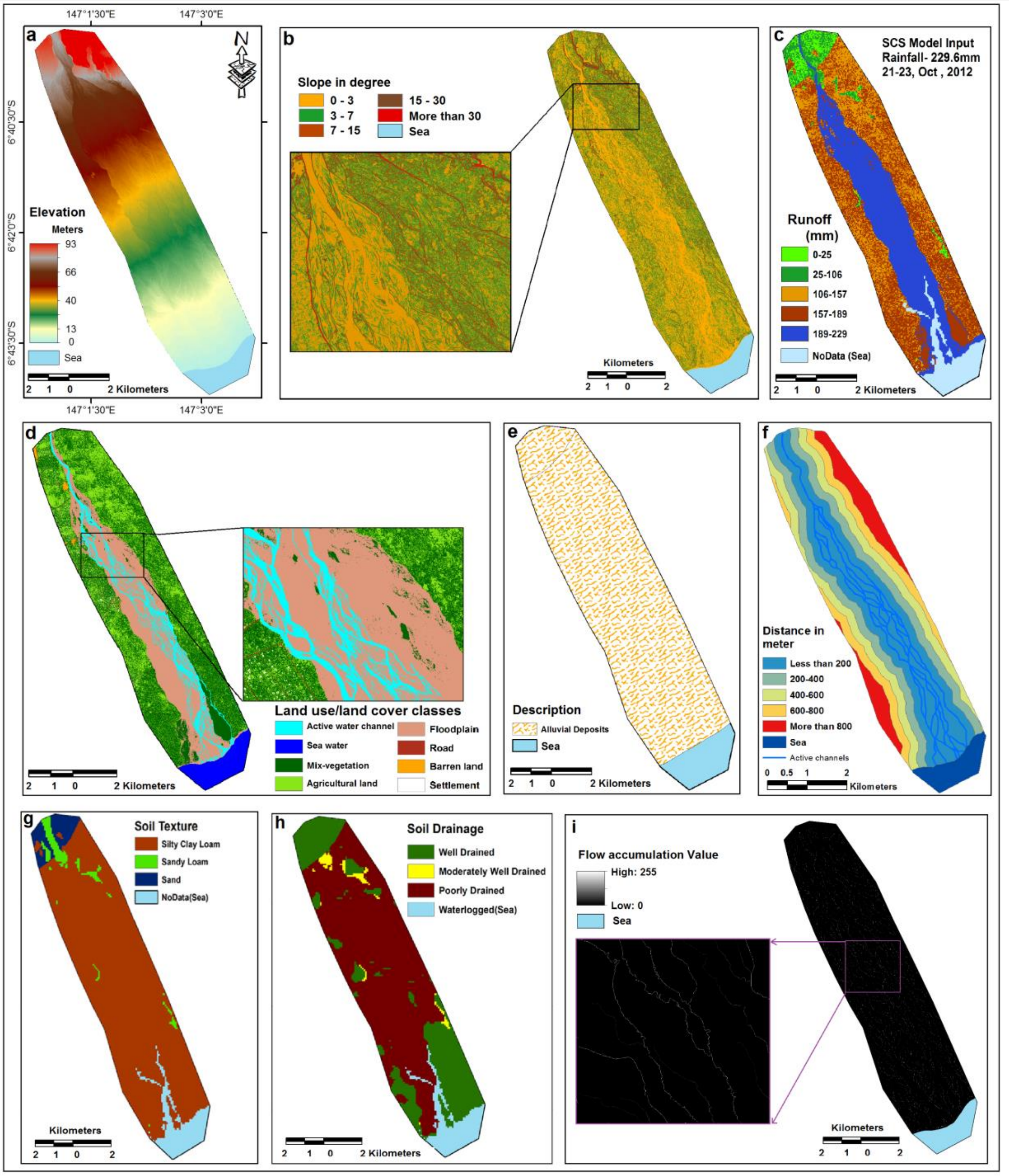

Figure 4: Spatial distribution of flood conditioning factors; (a)Elevation in meter, (b) Slope in degree, (c) Surface runoff through SCS model, (d) Land use/land cover characteristics, (e) Lithological characteristics, (f) Distance from active channels, (g) Soil texture, (h) Soil drainage and (i) Flow accumulation

Soil drainage naturally talks about the occurrence and period of wet epochs under circumstances like those under which the soil developed. Fabricated adjustments to the water system through drainage or irrigation do not have much impact on the soil except a considerable change is made to the soil. Four soil drainage classes are identified according to the water tables, their positioning in the landscape, their wetness, and their form and structures in the study area. These groups are well drained, moderately well drained, poorly drained, and waterlogged (sea) (Figure 4h). Flow accumulation is one of the flood factors considered in this flood risk assessment.

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The water from a cell flows towards the nearest down slope cell. Flow accumulation tools easily find out the accumulated flow with the known flow direction. All these methods concerning hydrology were performed using the hydrology tool extension in ArcGIS 10.5. The calculated flow accumulation values range from 0 to 255 (Figure 4i).

After the preparation of the input parameters different GIS models, like the Pairwise comparison, the ranking method, and the Boolean logic were used to develop flood susceptibility maps respectively. The resulting output through all the methods was reclassified into five (5) susceptibility zones, namely very high, high, moderate, low, and very low. Approximately 33.63% of the study areas are designated as very high susceptibility, 24.11% as high, 25.76% as moderate, 11.67% as low, and 4.83% as very low respectively through the Pairwise method (Table 6). The resulting data sets through the ranking method show 28.96% of the study areas as very high susceptibility, 18.14% as high, 23.40% as moderate, 21.22% as low, and 8.27% as very low respectively through the Pairwise method (Table 6). Most of the high susceptibility zones were identified in the middle portion and southern part of the study area where the active water channels are carrying water through it and empty into the Huon golf as per the resulting maps through the Pairwise method (Figure 5a) and Ranking method (Figure 5b) respectively. The Boolean logic derived a very significant result, which is very different from the first two methods. Only three classes were generated through the method, namely moderate (37.77%), low (39.95%), and very low (22.78%) respectively (Table 6 and Figure 5c).

Table 6: Statistical distribution of resulted flood susceptibility zones through Pairwise, ranking and Boolean logic

Flood susceptibility zones	Pairwise method		Ranking method		Boolean logic	
	Area (Km^2)	Percentage	Area (Km^2)	Percentage	Area (Km^2)	Percentage
Very high	5.69	33.63	4.90	28.96	0	0
High	4.08	24.11	3.07	18.14	0	0
Moderate	4.36	25.76	3.96	23.40	6.39	37.77
Low	1.98	11.67	3.59	21.22	6.76	39.95
Very low	0.82	4.83	1.40	8.27	3.77	22.28
Total	16.92	100.0	16.92	100.00	16.92	100.00

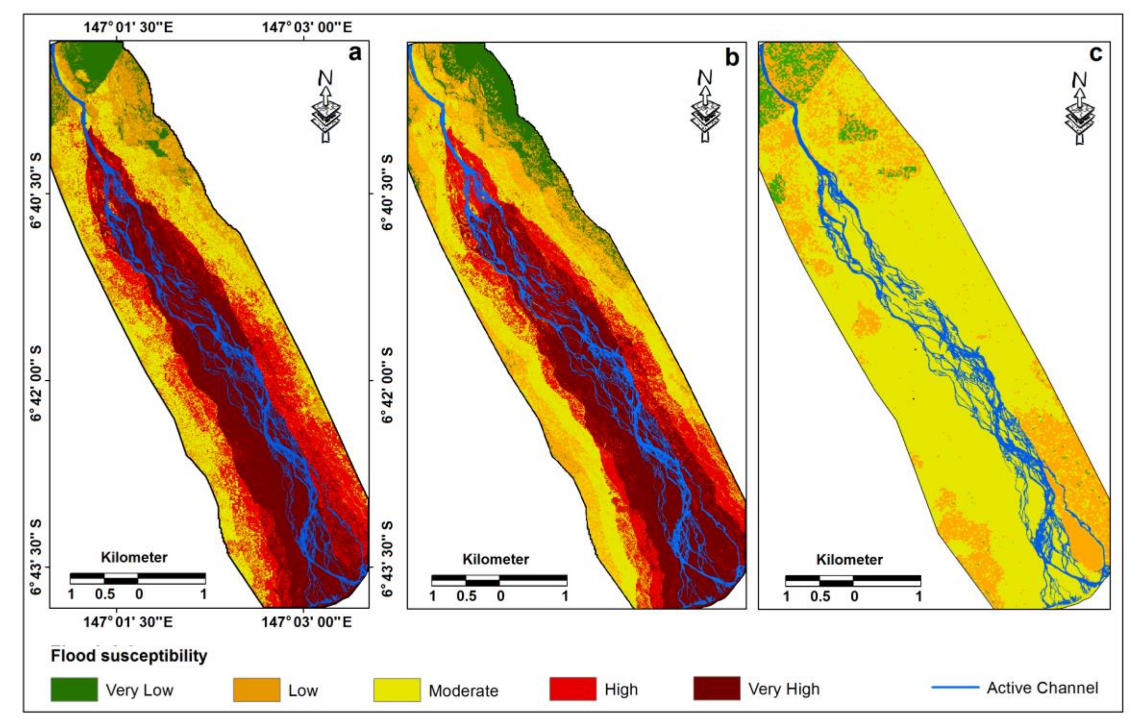

Figure 5: Flood susceptibility zone based on (a) Pairwise comparison, (b) Ranking and (c) Boolean logic

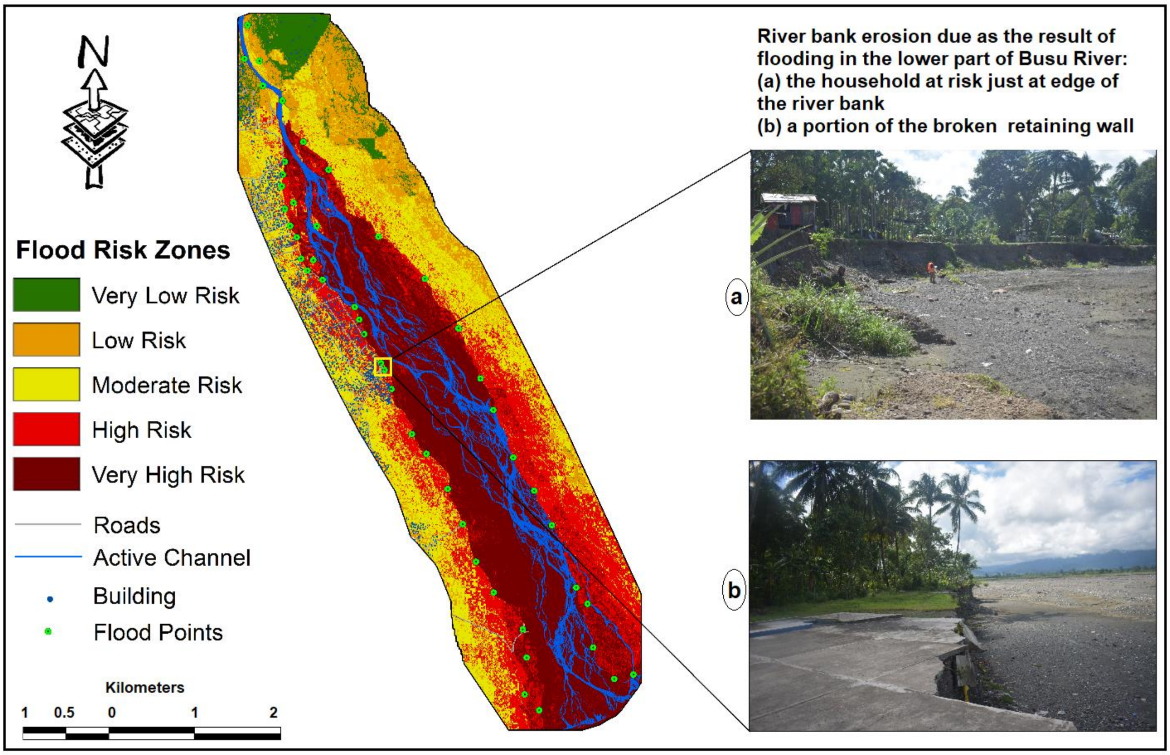

Figure 6: Historical flood points and building footprints on the flood susceptibility map through Pairwise comparison method

Table 7: Comparison of flood points against each flood susceptibility mapping technique

Flood susceptibility zones	Pairwise comparison	Ranking	Boolean logic
Very high	17	12	None
High	15	16	None
Moderate	9	11	12
Low	5	7	22
Very low	None	None	12
Total flood points	46	46	46

Table 8: Population at risk based on vulnerability assessment

Flood susceptibility zones	**Pairwise comparison**		**Ranking**		**Boolean**	
	Household	**Population**	**Household**	**Population**	**Household**	**Method**
Very high	11	55	17	85	None	None
High	226	1130	189	945	None	None
Moderate	1213	6065	1134	5670	340	1700
Low	483	2415	667	3335	936	4680
Very low	122	610	48	240	779	3895

Flood validation is simply to check the authenticity of flood susceptibility analysis by using the existing flood point or through field verification by visiting the flood scene in the study area. Model validation is a key topic in flood risk analysis, as flood risk assessments are characterized by significant levels of uncertainty [70]. Validation is to evaluate risk valuation precision with the use of vulnerable parameters to higher susceptibility zones. It is also important for decision-makers to make decisions. There are many validation approaches to perform using the concerned parameters. Forty six (46) historical flood points were used to validate the susceptibility mapping through different GIS models. An attempt was taken to show the historical flood points on the resulted output through Pairwise comparison method (Figure 5). The overlay analysis suggests that thirty-two (32) flood points falls within the very high and high susceptibility zones and nine (9) flood points on moderate and five (5) flood points on low flood susceptibility zone (Figure 6 and Table 7). The similar analysis was performed for other two methods (Table 7).

The population is the most important parameter when doing a flood risk assessment and flood validation, thus it is eminent to deliberate on the population in the flood hazard zone. The building footprints were captured from LiDAR 30cm spatial resolution data sets of the area. Population data were gathered from the country's national census and the national statistics office of Papua New Guinea. Alternatively, a survey was done around the Busu Plain to estimate the average household population. The survey suggests that on average five people are living in every household. The populations at risk were identified as per the degree of risk (Table 8). Figure 6 represents the building footprints on the resulted flood susceptibility zones derived through Pairwise comparison method.

5. Conclusions and Recommendation

The primary drive behind this work was to model inland floods using multiple approaches or multi-criteria analysis. Such approaches are; the Pairwise Comparison, the Ranking, and the Boolean logic, to establish flood assessment maps that identified areas that are likely to be affected by flooding and the degree of harm that can be caused to the local population. By using all the available data with the use of GIS software and other supplementary software, a better flood risk assessment was done which is user-friendly. These flood risk maps especially from Pairwise and Ranking can be used for flood mitigation and flood hazard preparedness. The MCA techniques offer a practicable approach for analyzing and implementing the influences of different factors, including multiple levels of contingent, autonomous, analytical, and measurable data after combining high-resolution satellite data (LiDAR), demographic data, topographic datasets, national soil data, and weather data. The DEM was used to categorize the areas of threat in the study vicinity. The defined flood impact parameters are precipitation, elevation and slope, geology, land-use land cover, soil, and other geomorphic characteristics. Thematic maps were generated by using various image analysis methods including specific GIS analysis using several GIS software. Each one of the thematic layers was analyzed by using the weighted overlay, weighted sum, and Boolean and operations to generate the final flood susceptibility maps. The weights are assigned by taking into account the flood susceptibility and vulnerability of the region. The three flood assessment maps generated were done using three different methods, namely Pairwise comparisons, Ranking and Boolean. In the Pairwise Comparison method, the criteria weights were generated by filling the comparison matrix, normalizing the matrix, and then calculated the priority vector. In order for the criteria weights to be accepted, a consistency analysis is done. In the Ranking method approach, the flood factors were reclassified and ranked. The ranking values are ranged from 1 to 5 according to their relative importance to the flood, where 1 is the very low risk and 5 is the very high risk. In the final method, Boolean logic the flood factors were reclassified again after the first reclassification. The second reclassification was done since Boolean operations only interpret integers. Boolean and operation was used for paired flood factors except Surface runoff. The validation process suggests the level of acceptability of each model used for flood susceptibility mapping after overlaying historical flood points on the resulted flood susceptibility database. Very high, high and moderate susceptibility zones were considered as positive for flooding zone, while on the other hand low and very low susceptibility zones were ignored for flooding. The analysis (Table 7) represents 41 (17 + 15 + 9) historical flood points falls within the positive flooding zone out of 46 historical flood points based on Pairwise comparison technique, which leads 89.13% accuracy. The accuracy of 84.78% and 26.09% were calculated for Ranking and Boolean logic respectively. The Boolean logic method is found not to be an accurate method for flood risk assessment as per the result compared to Pairwise comparisons and Ranking method.

Flood assessment maps are very vital as they generate a roadmap for the needed flood mitigation and preparedness methods. In all three approaches, the value of each factor was measured by determining how much each factor contributed to the flood. The monitoring and treatment of flood risk is fundamentally part of social and environmental growth, which targets reducing the loss of life, and natural and manmade resources that are of benefit to individuals. Flood Mitigation. Busu flood is real, real damages were done. The people living around the Busu River are victims of flood and have been living in fear for many years. The government authority must now consider both structural and non-structural flood mitigation measures. It is identified that even with considerable use of structural flood mitigation methods, the flood damages were still devastating due to the flood factors involved. The government must now initiate multifaceted flood management in Morobe Province as well as other parts of Papua New Guinea, by stretching out the use of nonstructural means of flood risk management. This study suggests that MCA is a better decision-making method and must be considered for better solutions by the local authority.

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