COASTAL FLOOD VULNERABILITY IN GHANA

What are the most vulnerable coastal districts to floods in Ghana?

BACHELOR THESIS

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Summary

Climate change poses a challenge to coastal cities in the world. As global coastal populations are estimated to grow in the face of rising sea levels and changing precipitation patterns coastal cities are becoming increasingly vulnerable to floods. Ghana has a coastline of approximately 560km which yearly experiences coastal flooding due to these climate change-induced flood hazards. For this reason, this study seeks to assess coastal flood vulnerability in Ghana at a district level to answer the central question *What are the most vulnerable coastal districts to floods in Ghana?* This study adopts the indicator approach using the Multi-Criteria Decision Analysis(MCDA) based on an Analytical Hierarchy Process (AHP) to determine the weights in addition to geoprocessing tools in a GIS environment to generate a Coastal Flood Vulnerability Index of the coastal districts of Ghana. The results indicate that the Ketu South Municipality is the most vulnerable coastal district to floods with a mean index of 3.8 indicating high vulnerability to floods. This research would help policymakers address the ongoing problem of floods in the coastal districts of Ghana by providing a basis for flood impact mitigation.

Keywords Coastal Flood Vulnerability, Ghana, AHP, MCDA, Physical Flood Vulnerability, Social Flood Vulnerability, GIS.

Introduction

Climate change is a well-researched issue in the world today. The effects of this include storm surges, rising sea levels, changing precipitation patterns, and many others which may increase the vulnerability of coastal dwellers to floods. This problem poses several challenges to coastal cities in the world and especially to developing countries like Ghana. According to the UNISDR (2011), 70 million people are exposed to floods and this number is estimated to increase in the future as the global coastal population is expected to increase from 1-1.4 billion by 2060 (Neumann et al., 2015) which would increase the number of people at risk of floods. To reduce the probable effects of this problem, vulnerability assessments are often used as a major step toward ensuring disaster reduction (Roy and Blaschke, 2015). Analyzing flood vulnerability is important because coastal areas are particularly susceptible to climate-influenced disasters (Roy and Blaschke, 2015). It helps decision-makers to adopt strategies to reduce the impact of floods on the citizens. It could additionally inform decision-makers on which areas should receive more investment for disaster prevention (Roy and Blaschke, 2015).

Research Problem

In Ghana, there has been an increase in coastal floods due to storm surges, tidal wave flooding, and heavy torrential rainfall (Babanawo et al, 2023) which has often led to the loss of lives and properties. In the face of this problem, there is however little spatially explicit flood vulnerability research conducted in coastal regions of Ghana. Most research on this issue was conducted in Accra (Yankson et al., 2017; Atakorah et. al, 2023) which is known to have 71% of the metropolis susceptible to floods. Others focus only on the delta and estuary areas of Ghana (Babanawo et al, 2023; Ofosu et al., 2020). In addition, the majority of the existing body of research focuses on the physical vulnerability assessment which overlooks the socio-economic impact of floods (Babanawo et al, 2023). Also, most research on this topic is mostly on lower spatial resolution. For example, Dada et al. (2024) assessed coastal flood vulnerability but on a West African spatial level. For this reason, this research aims to contribute to flood vulnerability research by conducting a flood vulnerability assessment in all 31 coastal districts of Ghana. This research seeks to answer the central question; *what are the most vulnerable coastal districts to floods in Ghana*?

In addition, this research aims to answer the following sub-questions.

What are the most physically vulnerable coastal districts to floods in Ghana?

What are the most socially vulnerable coastal districts to floods in Ghana?

What are the advantages and limitations of using an MCDA-based AHP model in assessing coastal flood vulnerability in Ghana?

Thesis Structure

The next section delves into the theoretical and conceptual underpinning of this study. After that, the data and methodology outline the various datasets and methods used in conducting this research. This is followed by the findings of the study. This is followed by the conclusions, limitations, and recommendations of this study.

Theoretical Framework

Concepts and Theories in Flood Vulnerability Studies

a. Hazard, Exposure, Susceptibility and Coping Capacity

The concept of hazard is central to vulnerability studies. Since this study is concerned with flood vulnerability, the natural hazard of interest is flooding. White et. al (2005) defined vulnerability as the interrelation between exposure, susceptibility, and coping capacity. It is the degree to which a system, subsystem, or its components are exposed to stress or perturbation (Turner et al., 2003). Exposure in flood vulnerability research deals with how much an object is in contact with the hazard. Susceptibility entails how sensitive or resistant to the effects of a flood (Fernandez et al. 2016) while coping capacity can be described as the recovery potential or resilience (Fernandez et al. 2016). Smit and Wandel (2006) argued that exposure and the susceptibility of the system are influenced by an interaction of the environment and social forces while the coping capacity is shaped by socioeconomic, cultural, and political factors.

b. Physical and Social Vulnerability

Coastal flood vulnerability studies used in assessing climate change-influenced flood hazards are studied under one or more of the three main theoretical pillars namely bioecological, physical, and social vulnerability. For our research, social vulnerability and physical vulnerability will be the most important. Bioecological vulnerability often deals with how ecosystems are prone to the effects of floods and their impacts on ecosystem services (Bevacqua et al., 2018). Physical vulnerability is the "combination of the predisposition of the exposed elements to suffering damage and the potential of natural hazards to cause damage" (Leal et al, 2021: page 2). This is a popular approach to evaluating vulnerability in traditional flood risk assessment studies (Kind et al., 2020). Under this, vulnerability is assessed using physical factors that expose a society to the hazard (Mattah et al., 2023). Deepak et al., (2020) combined several different physical-environmental indicators to assess vulnerability. Their rationale was that physical vulnerability is concerned primarily with the susceptibility to floods. Unlike social vulnerability, physical vulnerability to flood hazards could be the same for all the people exposed to the hazard (Deepak et al., 2020). However, other authors who assess physical vulnerability view through the lens of damage to assets using hydrological flood modeling and damage curves to estimate the maximum potential damage based on the water depth of the flood (Kind et al., 2020; Leal et al, 2021; Zhou et al., 2021). This approach requires the user to have a lot of data on the building types, building floor levels, building materials costs, damage curves, and an in-depth knowledge of hydrological modeling. Due to the unavailability of publicly accessible data on this, the indicator approach would be adopted for this research to assess physical vulnerability.

Social vulnerability to hazards was pioneered by Cutter et al, (2003) who argued that vulnerability to hazards is a result of the inequalities that exist within social groups which influence their susceptibility and coping capacity to disasters like floods. They indicated that these inequalities could arise because of place inequalities which could be influenced by physical factors. Kind et al. (2020) defined social vulnerability to floods as “the consumption lost in a year after a flood (accounting for financial protection), as a fraction of annual income” (Kind et al., 2020: page 120).

c. Vulnerability Index

One of the most used ways of estimating vulnerability is using a vulnerability index (Ajtai et al., 2023). This is based on an indicator approach that combines various variables that influence vulnerability (Ajtai et al., 2023). For physical vulnerability, the index would be based on different physical indicators that make people susceptible to floods as indicated by Deepak et al. (2020). Social vulnerability to floods index on the other hand is normally assessed using the method propounded by Cutter et al. (2003) which combines several socio-demographic variables to create a vulnerability index to a natural hazard. This approach has been modified over the years to include weights since various variables may have more impact on vulnerability than others (Ajtai et al., 2023). Since physical and social vulnerability are interlinked due to place inequalities (Cutter et al, 2003), this research seeks to combine both theories into a coastal assessment of flood vulnerability of the coastal districts of Ghana using GIS to combine both vulnerabilities into a single index which would be expanded upon in the methodology and results sections of this paper.

Conceptual Model

The various concepts and theories explored in the previous section are summarized in the conceptual model below which shows the relationship between the various concepts and theories outlined in the theoretical framework. The hazard in this model is the flood event which could arise because of rainfall, storm surges, or tidal forces. The social and physical flood vulnerability are interlinked because of the findings of Cutter et al, (2003) who demonstrated in their paper how the two theories often influence each other for exposure, susceptibility, and coping capacity. Also, based on Smit and Wandel (2006) the interaction of social and environmental factors influences susceptibility and exposure while socioeconomic, cultural, and political factors influence the coping capacity.

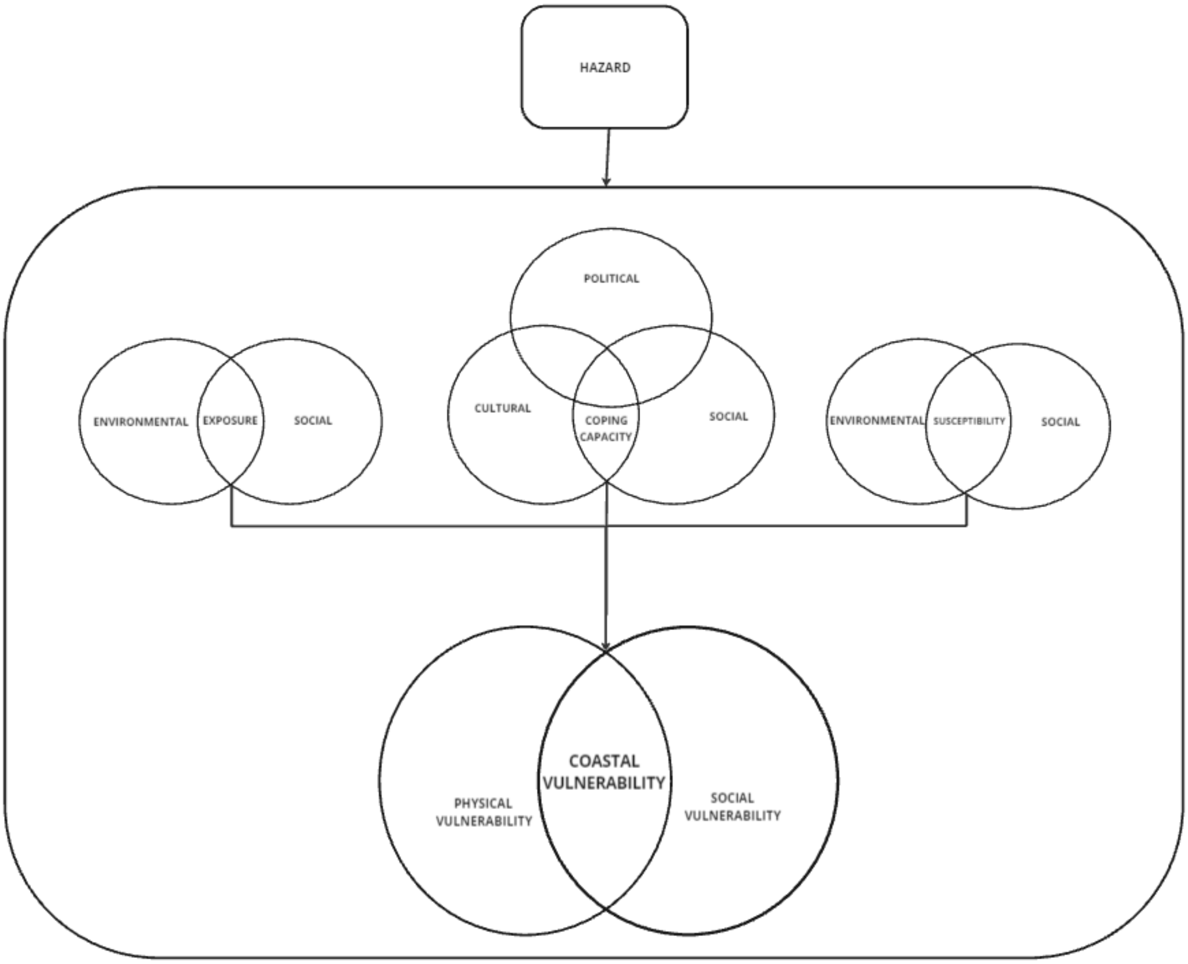

Figure 1: Conceptual Framework

Data and Methodology

Data

This research aims to answer the central question *what are the most vulnerable coastal districts to floods in Ghana*?

To answer this question, a coastal flood vulnerability index was generated incorporating both the physical flood vulnerability and the social flood vulnerability in the study area. For the social flood vulnerability, data on the Ghana Population and Housing Census 2021 which contains data on the number of persons per district with some level of disabilities, age, gender, employment status, health insurance coverage, and education (see Table 7 in the appendix).

Data Management and Ethics

These datasets are openly available to use strictly for academic purposes. These datasets were already aggregated to a lower spatial resolution to ensure they meet the privacy and GDPR of the EU. The datasets were downloaded datasets on a local encrypted drive throughout the duration of the research. To ensure the research data was not lost in case of technical issues or breaches. The data was backed up on the author's Microsoft OneDrive to ensure that any technical setbacks would not heavily setback this research.

Methodology

This research uses a Multi-Criteria Decision Analysis(MCDA) framework in carrying out flood vulnerability analysis. Within this framework, an Analytical Hierarchical Process (AHP) propounded by Saaty (1980) is adopted. This method is a structured technique that allows the user to determine the relative importance of various variables systematically (Vignesh et al., 2021) which is coupled with geospatial technologies specifically ArcGIS Pro as the main GIS environment used in the preparation, processing, and analysis of the various datasets described in the table above. To prepare the dataset for use in the AHP, first, the data had to be reclassified into five classes ranging from 1 which indicates the lowest vulnerability to 5 indicating the highest vulnerability. These classes are outlined in Table 1 and the rationale behind the reclassification is expanded on in the next section for both the physical and the social flood vulnerability variables below.

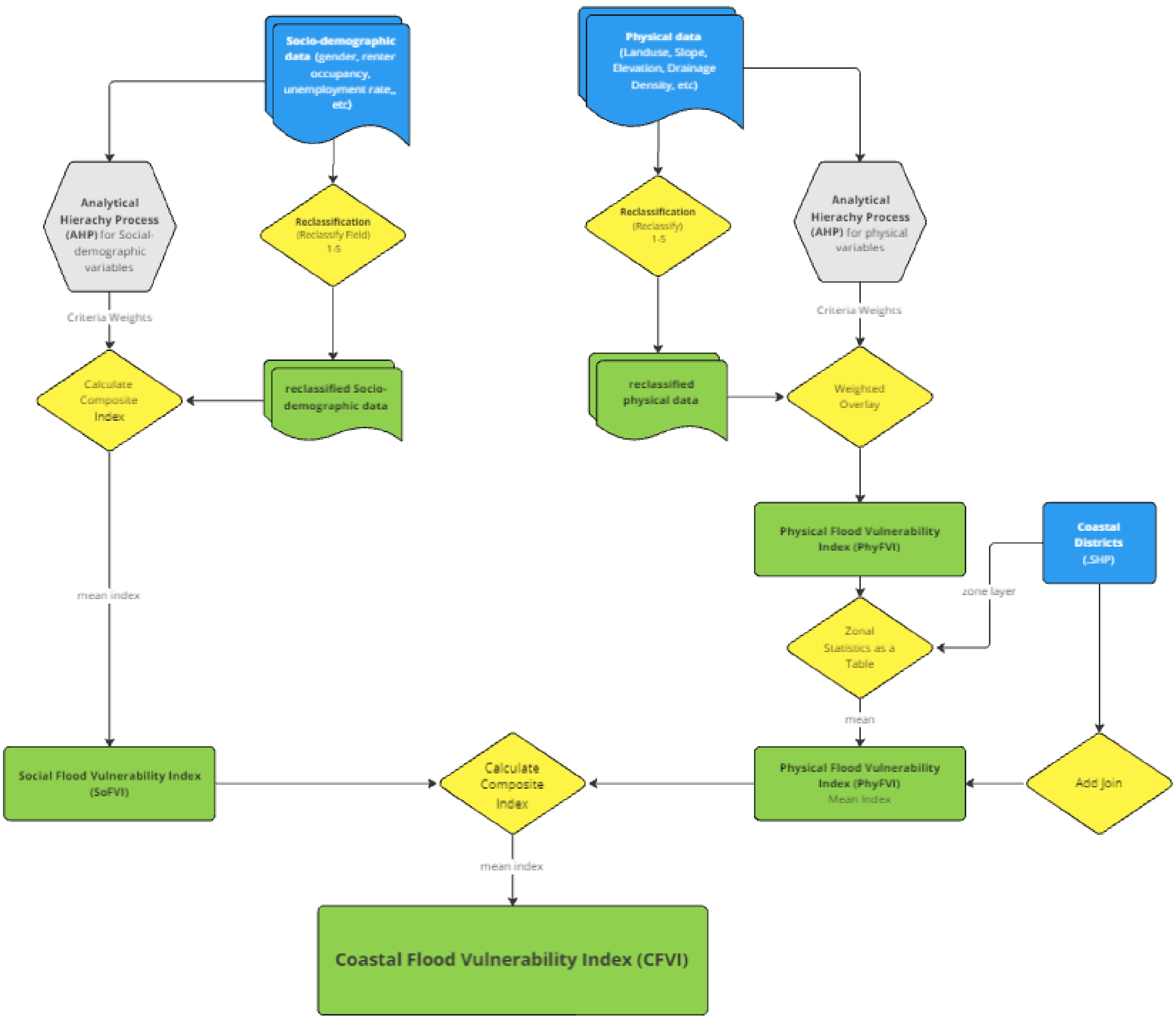

Figure 2: Methodological Framework of the research.

Physical Flood Vulnerability Variables

a. Landuse

The WorldCover V2 data retrieved from the European Space Agency was clipped to the study area using the Clip Raster geoprocessing tool in ArcGIS Pro. The various land use types were reclassified using the Reclassify geoprocessing tool. Since land with no vegetation cover is more susceptible to floods (Machado et al., 2019), Tree Cover was classified as lowest (1), Shrubland and Grassland as low(2), Cropland as moderate (3), Mangroves, Built-up and Bareland as high(4) and lastly Permanent Water and Herbaceous Wetland as the highest (5)

b. Slope

This slope data was generated from the void-filled DEM using the Slope geoprocessing tool in ArcGIS Pro to calculate the percent rise. After this, the Reclassify tool was used to reclassify the slope values from lowest(1) to highest(5). 0 to 10% was classified as the highest(5), 20%-30% as moderate (3) while slope values greater than 40% were classified as the lowest(1).

c. Elevation

The DEM retrieved from Hydrosheds was also reclassified using the Reclassify geoprocessing tool in ArcGIS Pro. Since higher elevation is less susceptible to flooding, using the natural breaks algorithm, elevation values between -28m to 19.2m were classified as the highest (5) while 43.6m to 72.2m were classified as moderate (3) and elevation values more than 105.1m were classified as lowest(1)

d. Topographic Wetness Index (TWI)

The TWI was calculated using the DEM. First, the degrees slope was calculated using the Slope geoprocessing tool in ArcGIS Pro. The flow direction and flow accumulation were calculated using the Flow Direction and Flow Accumulation tools respectively in the GIS software. Next using the Raster Calculator, the radians of slope (β) were calculated by multiplying the degree slope with 1.570796 and dividing the result by 90. The tan slope was calculated using the raster calculator. Likewise, the flow accumulation data was scaled to the cell size(a). Lastly, the TWI was calculated by using $\ln(a / \tan(\beta))$. After the calculation of the TWI, the values were reclassified using the Reclassify tool employing the natural breaks algorithm in ArcGIS Pro in 5 classes. The index values from -6.5 to -3.9 were classified as the lowest, -2.8 to -1.5 as moderate, and 0.3 to 6.1 as the highest.

e. Average Precipitation

The monthly precipitation rasters in the dataset were summed up and their total was divided by 12 to get the average yearly precipitation using the Raster Calculator. Next, it was clipped to the area of study and classified using the Reclassify geoprocessing tool. Since the higher the precipitation, the greater the risk of floods, this dataset was classified into 5 classes namely 67-90(lowest), 90-105(low), 105-122(moderate), 122-142(high), 142-165(highest).

f. Drainage Density

The drainage density was calculated by using the Flow Accumulation raster calculated from the DEM. By using the Raster calculator, a threshold value of 10000 was applied to filter out the less prominent stream channels from the mainstream channels. The output of this was converted to a vector dataset using the Raster to Polyline geoprocessing too to define the stream channels within the study area. Using the line density geoprocessing tool, the drainage density was computed in km^2 with a raster output. This drainage density was reclassified as 1.5-4.9 (highest), 4.9-7.2(high), 7.2-9.8(moderate), 9.8-13.1(low), and 13.1-18.0(lowest). This classification was adapted to Vignesh et al. (2020) which flood vulnerable zones with low density and less vulnerable zones with high density.

Social Flood Vulnerability Variables

a. Gender

According to Cutter et al (2003), due to sector-specific employment, lower wages, and family care responsibilities, women can have a more difficult time recovering after a natural hazard like a flood. For this reason, the indicator total number of women per district was used in this research. This was then reclassified using the Reclassify Field geoprocessing tool in ArcGIS Pro to 5 classes as illustrated in the appendix (Figure 13).

b. Average Household Size

According to Mruksirisuk et al. (2023) demonstrated a high correlation between flood vulnerability and household size. They said, “Larger household size faces greater challenges in times of flooding, such as evacuation, locating suitable shelter, and meeting basic needs.”- Muksirisuk et al. (2023; pg 11). Using the prior geoprocessing tool, this indicator was reclassified into 5 classes using equal intervals as illustrated in the appendix (Figure 14).

c. Age Dependency Ratio

This indicator was added to the model because the event of a flood affects the livelihood of residents (Babanawo et al 2023) which could increase the pressure to provide for people dependent on them. For that reason, this indicator was added also reclassified into the 5 classes using equal intervals.

d. Purchasing Power Per Capita (PPPC)

High income is associated with having a close relationship to flood sensitivity as people with higher incomes can adapt well in the face of a flood event making them less vulnerable (An et al, 2022). For this reason, this indicator was included in the model and reclassified using natural breaks from 1 to 5 with higher PPPC resulting in a lower vulnerability and lower PPPC with higher vulnerability.

e. Unemployment rate

Cutter et al (2003; pg 247) argued that “the potential loss of employment following a disaster exacerbates the number of unemployed workers in a community, contributing to a slower recovery from the disaster”. This indicates a higher social vulnerability to floods if the unemployment rate is high within the district. Likewise, this was also reclassified as depicted in the appendix (Figure 17).

f. No Health Insurance Coverage

Access to medical services is crucial post-flood as floods could lead to physical harm to people which leads to the need for immediate medical services (Du et al, 2010). Babanawo et al (2023) noted that flood events in Ghana are also associated with health implications with a surge in waterborne diseases such as Cholera, Malaria, and many others. Since livelihoods are affected during a flood event (Cutter et al., 2003), having health insurance would alleviate the health challenges associated with floods. This dataset was reclassified with a higher number of persons with no health insurance as more vulnerable and then less number of people as detailed in Table 9 (see appendix).

g. Physical Disabilities

Cutter et al., (2003) indicated that people with disabilities are disproportionately affected during a natural disaster, and due to their invisibility in their communities, they tend to be ignored in the event of a natural disaster such as a flood. Persons with physical disabilities are highly vulnerable to natural hazards as they are mostly at risk of getting injured during the hazard (Bronfman et al., 2021). Therefore, the higher the number of persons with physical disabilities, the more vulnerable the district would be hence this data was reclassified from 1 (lowest) to 5 (highest) using the natural breaks algorithm.

h. Renter Occupancy

According to Cutter et al. (2003; pg 247), “People that rent do so because they are either transient or do not have the financial resources for home ownership. They often lack access to information about financial aid during recovery. In the most extreme cases, renters lack sufficient shelter options when lodging becomes uninhabitable or too costly to afford”. This means that districts with more renters are more socially vulnerable to floods than those with less renters. Hence, this indicator was reclassified with natural breaks from 1 (lowest) to 5 (highest) as outlined in Table 9 (see appendix).

i. Educational Attainment

Educational attainment is often linked to a higher socioeconomic status which leads to greater lifetime earnings (Cutter et al., 2003). This research focused on post-secondary school education as a measure of educational attainment considering the number of people who fall into this category. The higher the number of people with post-secondary education, the lower the social vulnerability of the district to floods. This was used to reclassify the dataset as depicted in the map below and outlined in Table 9 (see appendix) for each coastal district.

Analytical Hierarchy Process (AHP)

An AHP-based pairwise comparison matrix was used to assign varied weights to our indicators for both the physical and social flood vulnerability variables. This is done based on their relative importance on a scale of 1 to 9 (Figure 3) as propounded by Saaty (1980). These values range from less importance to more importance based on how they influence floods (Vignesh et al. 2021). To get the normalized pairwise matrix, each cell is divided by the column total of each variable. Lastly to get the Criteria Weights, the normalized value in each variable row is summed up and divided by the total number of criteria.

Numerical rating	Verbal judgments of preferences
9	Extremely preferred
8	Very strongly to extremely
7	Very strongly preferred
6	Strongly to very strongly
5	Strongly preferred
4	Moderately to strongly
3	Moderately preferred
2	Equally to moderately
1	Equally preferred

Figure 3 Pairwise Comparison Scale by Saaty (1980) (Source: Vignesh et al. 2021; page 775)

	Landuse	Slope (%rise)	Elevation (m)	TWI	Average Precipitation (mm)	Drainage Density
Landuse	1	1	2	2	2	1
Slope (% rise)	1	1	2	3	3	1
Elevation (m)	0.5	0.5	1	3	3	3
TWI	0.5	0.33	0.33	1	3	2
Average Precipitation (mm)	0.5	0.33	0.33	0.33	1	3
Drainage Density	1	0.33	0.33	0.5	0.33	1
TOTAL	4.5	3.49	5.99	9.83	12.33	11

Table 1 Pairwise comparison matrix of 6 x 6 decision matrix for physical flood vulnerability

	Land use	Slope	Elevation	TWI	Average Precipitation	Drainage Density	Criteria Weights
Land use	0.216536	0.2470085	0.4141823	0.262538463	0.21605326	0.090067949	0.21653648
Slope	0.216536	0.2470085	0.4141823	0.393807694	0.32407989	0.090067949	0.247008547
Elevation	0.108268	0.1235043	0.2070912	0.393807694	0.32407989	0.270203848	0.207091162
TWI	0.108268	0.0815128	0.0683401	0.131269231	0.32407989	0.180135899	0.131269231
Average Precipitation	0.108268	0.0815128	0.0683401	0.043318846	0.10802663	0.270203848	0.10802663
Drainage Density	0.216536	0.0815128	0.0683401	0.065634616	0.035648788	0.090067949	0.090067949
						∑=1.0000	

Table 2 Normalized pair-wise comparison 6 x 6 matrix for physical flood vulnerability

Consistency Check

The criteria weights derived from the AHP were tested using the Consistency Ratio (CR) to ensure the consistency of the allotted weights (Saaty, 1980). To achieve this, the CR must be below 0.1 for the weights to be acceptable. The result indicated that the consistency of the Eigen vector-matrix achieved a CR index of 0.099 for the physical flood vulnerability matrix while the CR for the social flood vulnerability was 0.095 indicating the criteria weights generated for the analysis are acceptable and are consistent. The formula for the CR is outlined below.

$CR = CI / RI$,

where CR is the consistency ratio, CI is the consistency index, and RI is the random index. The consistency index is calculated using the formula below.

$CI = (\lambda_{max} - n) / (n - 1)$,

where λ_{max} is the principal eigenvalue calculated by dividing the weighted sum vector by the total number of variables, while n is the total number of variables or criteria. The value of the RI is based on the size of the matrix. Since the physical flood vulnerability, is a 6 x 6 matrix while the social flood vulnerability uses a 9 x 9 matrix, an RI of 1.24 and 1.45 was used for physical and social flood vulnerability respectively as indicated in Table 3.

Size of Matrix (n)	1	2	3	4	5	6	7	8	9	10
Random Index (RI)	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49

Table 3 Random Index (RI) Table

	Gender	Average Household Size	Age Dependency Ratio	Purchasing Power Per Capita	Unemployment Rate	No Health Insurance Coverage	Physical Disabilities	Renter Occupancy	Educational Attainment
Gender	1	2	2	2	3	2	2	4	5
Average Household Size	0.50	1	3	3	2	2	2	3	4
Age Dependency Ratio	0.50	0.30	1	3	3	2	2	4	4
Purchasing Power Per Capita	0.50	0.33	0.33	1	4	2	4	4	5
Unemployment Rate	0.33	0.50	0.33	0.25	1	3	4	4	5
No Health Insurance Coverage	0.50	0.50	0.50	0.50	0.33	1	2	2	3
Physical Disabilities	0.50	0.50	0.50	0.25	0.25	0.33	1	3	5
Renter Occupancy	0.25	0.33	0.25	0.25	0.25	0.50	0.33	1	2
Educational Attainment	0.20	0.25	0.25	0.20	0.20	0.20	0.20	0.50	1
TOTAL	**4.28**	**5.71**	**8.16**	**10.45**	**14.03**	**13.03**	**17.53**	**25.50**	**34.00**

Table 4 Pairwise comparison of 9 x 9 decision matrix for social flood vulnerability

	Gender	Average Household Size	Age Dependency Ratio	Purchasing Power Per Capita	Unemployment Rate	No Health Insurance Coverage	Physical Disabilities	Renter Occupancy	Educational Attainment	Criteria Weights
Gender	0.233	0.350	0.245	0.191	0.214	0.153	0.114	0.157	0.147	0.201
Average Household Size	0.117	0.175	0.367	0.287	0.143	0.153	0.114	0.118	0.118	0.177
Age Dependency Ratio	0.117	0.053	0.122	0.287	0.214	0.153	0.114	0.157	0.118	0.148
Purchasing Power Per Capita	0.117	0.058	0.040	0.096	0.285	0.153	0.228	0.157	0.147	0.142
Unemployment Rate	0.078	0.088	0.041	0.024	0.071	0.230	0.228	0.157	0.147	0.118
No Health Insurance Coverage	0.117	0.088	0.061	0.048	0.024	0.077	0.114	0.078	0.088	0.077
Physical Disabilities	0.117	0.088	0.061	0.024	0.018	0.026	0.057	0.118	0.147	0.073
Renter Occupancy	0.058	0.058	0.031	0.024	0.018	0.038	0.019	0.039	0.059	0.038
Educational Attainment	0.047	0.044	0.031	0.019	0.014	0.015	0.011	0.020	0.029	0.026
									∑=1.0000	

Table 5 Normalized pair-wise comparison 9 x 9 matrix for physical flood vulnerability

Findings

Physical Flood Vulnerability Index (PhyFVI)

The outcome of the MCA revealed that 1.06 km^2 of the total area of the coastal districts had the lowest PhyFVI of 1. This means that 0.01% of the coastal districts were least physically vulnerable to floods. 5.21% of the districts recorded an index of 2 which represents low physical vulnerability to floods. It covers 467.44 km^2 of the entire study area. the most recorded PhyFVI was 3 which represents a moderate physical vulnerability to floods. This represented 68.31% of the total study area and covers an area of 6132.51 km^2. An area of 2361.37 km^2 recorded a high (4) PhyFVI which accounts for 26.30% of the total area of coastal districts in Ghana. Lastly, 15.54 km^2 of the study area recorded the highest physical flood vulnerability in the study area representing 0.17% of the total study area.

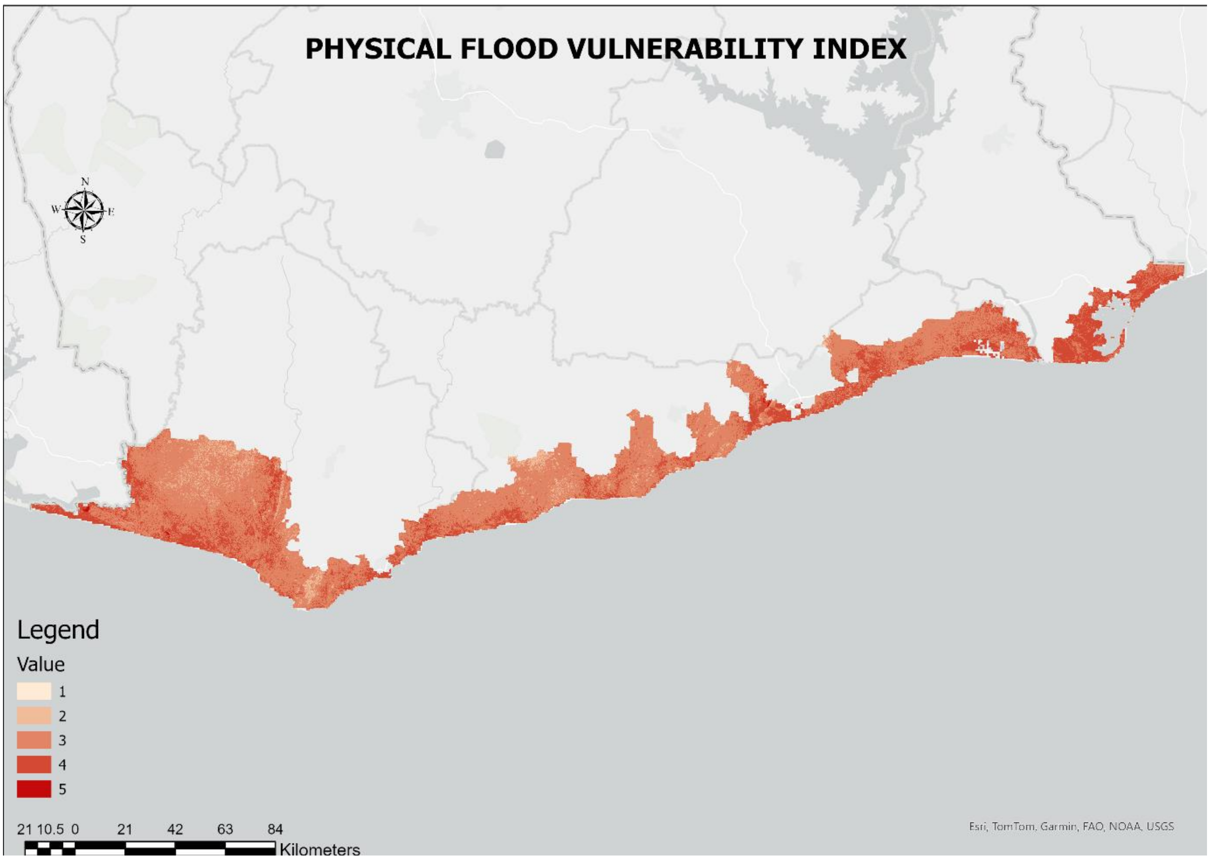

Figure 4: Map of Physical Flood Vulnerability Index (PhyFVI)

However, when aggregated at a district level the highest index is 3.96 which is in the Ablekuma West Municipality. This district borders the Densu flood plains which get inundated every high tide or during a storm surge or heavy rainfall. The Glefe lagoon situated in this district has been known to flood frequently (Frick-Trzebitzky et al, 2017) since it is part of what has often been a heated dispute between the municipality and residents in the area due to demolition exercises which have often been one of the flood management approaches used by state agencies like the Ablekuma West Municipal Assembly (Amoako et al, 2019). This is also because this delta has been designated as a Ramsar site protected under the Ramsar Convention since 1992. The outcome of this index is consistent with the findings of Frick-Trzebitzky et al (2017) who assessed flood risk in the Densu delta area identifying the Glefe as losing approximately 1 meter per year between 2005 to 2011 to coastal erosion which consequently increased flood risk in the area.

Besides, the second most physically vulnerable coastal district is the Accra Metropolitan Area with a mean aggregated index of 3.81. This district has been affected by floods since the 1990s (Yankson et al., 2017). It experienced one of the most devastating floods in recent years on June 3rd, 2015 which resulted in 150 casualties (Yankson et al., 2017). Several research has been conducted in this district to assess the factors behind this. Douglas et al (2008) attributed this to the observed rainfall patterns change since the 1980s. Yankson et al., (2017) also attributed to the poor non-integrated drainage system. This could be linked to the political dimension of vulnerability as the government and metropolitan assemblies are responsible for drainage provision and maintenance in Ghana. Dekongmen et al. (2021), attributed the floods to the drainage density and slope of the district. This is consistent with the findings of this research since both variables were considered in this research. Finally, the district with the third highest PhyFVI is Keta Municipal with a mean index of 3.80 also indicating a high physical vulnerability to floods.

On the other hand, the mean lowest PFVI is 2.82, 3.01, and 3.06 for the Abura Asebu Kwamankese, Mfantsiman Municipal, and Gomoa East respectively. Abura Asebu Kwamankese District is also home to the deciduous tropical rainforest in the northern part most prominent of them is the Kakum National Park which is a protected forest area. Floods are less likely to occur which is consistent with the findings of Machado et al (2019) which showed that areas with no vegetation cover are more likely to be at risk of floods.

Social Flood Vulnerability Index (FSoVI)

The result of the composite index revealed a mean index range of 1.1 to 3.9 in the coastal districts of Ghana. It revealed that the most socially vulnerable coastal district to floods in Ghana is the Ketu South Municipality with a mean index of 3.95 which indicates a high social vulnerability to floods. Babanawo et al (2022) demonstrated high flood sensitivity scores in the various communities within this district which is consistent with this research. A study on the perspectives of factors that influence flood vulnerability in the district revealed that weak demographic groups, low-income levels, and low educational levels were some of the main factors that socially influence flood vulnerability in the district (Babanawo et al., 2023). The next two districts with the highest FSoVI were Ga South and Gomoa East municipalities with an index of 3.61 and 3.41 respectively indicating a moderate to high vulnerability to floods within these coastal districts. In all, 6.5% of the total districts recorded a high SoFVI (index>3.4).

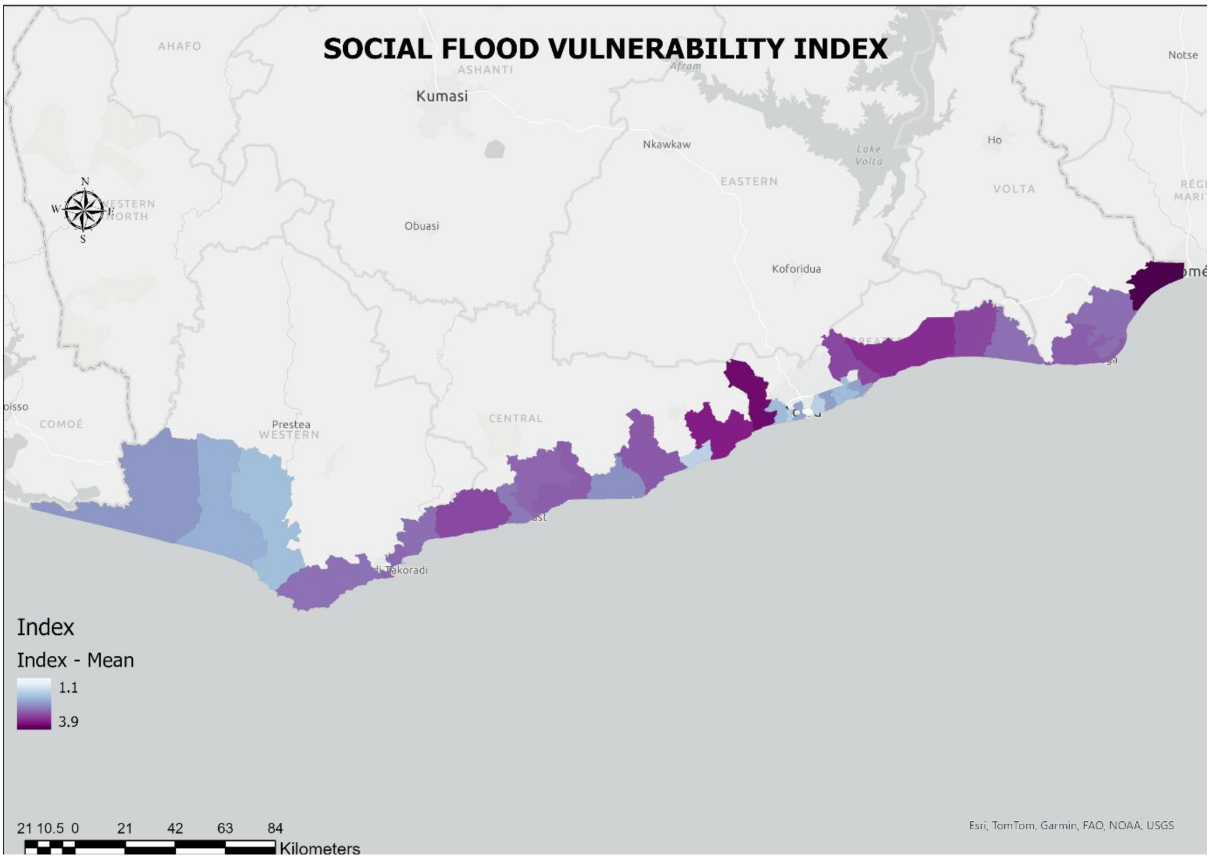

Figure 5: Map of Social Flood Vulnerability Index (SoFVI)

Additionally, the relationship between the various variables and the index was calculated using Pearson's Rho correlation. The results showed that all the variables had a positive correlation with the index except the renter occupancy variable. The average household size, persons with physical disabilities, and purchasing power per capita had a strong positive correlation of 0.69, 0.62, and 0.60 respectively indicating a strong linear relationship between the variable and the index. The variable with the weakest positive linear relationship is educational attainment with a correlation of 0.24 as indicated in the table below. However, the renter occupancy had no linear relationship with the index.

Indicator	Correlation with Index (r)
Educational Attainment (post-secondary education)	0.24
Renter Occupancy	0.00
Gender (Females)	0.36
Average Household Size	0.69
Age Dependency Ratio	0.52
Unemployment Rate	0.49
Persons with Physical Disabilities	0.62
No Health Insurance Coverage	0.45
Purchasing Power Per Capita	0.60

Table 6 Correlation between variables and FSoVI

Coastal Flood Vulnerability Index (CFVI)

The PFVI and the FSoVI were combined to produce the CFVI of the districts in Ghana. It resulted in Ketu South District as the most vulnerable coastal district in Ghana with a mean index of 3.78. This indicates a high flood vulnerability within the district. These findings are consistent with the findings of Babanawo et al (2023) which attributed flood vulnerability to various biophysical like low land elevation, inadequate coastal sea defense structures, and socio-economic factors which were discussed during the outcome of the FSoVI. In their research, respondents indicated that although there is a coastal flood defense system, the communities are frequently affected by floods. Flood exposure in this district could reach up to approximately 110.5cm which indicates that exposure within this district is already high (Babanawo et al, 2023). Also, it was indicated that economic activities within the district are affected during a flood event which prevents people from working till the flood waters drain (Babanawo et al 2023) impacting their livelihood. The outcome of this research also aligns with the findings of the authors who also attributed social vulnerability to high age dependency rates, low-income households, low educational attainment, and many others were the primary social factors influencing flood vulnerability. This is consistent with the Index based on its correlation with the FSoVI as outlined in the table above. Besides, the next two districts with the highest FSoVI are the Ga South Municipal and Anloga districts with indexes of 3.46 and 3.41 indicating a moderate to high vulnerability to floods in Ghana. It is interesting to note that three of the four highest CFVI were all districts located in the Volta River estuary. This aligns with various studies (Mattah et al., 2023) and news articles (Joy Online, 2021) written about this district. For example, Mattah et al., (2023) found high exposure and sensitivity to floods within communities in this area which leads to high vulnerability. On the other hand, the least vulnerable coastal district to floods is the Korle Klottey Municipality with a mean CFVI of 2.33 representing a low vulnerability to floods. Effutu Municipal District and La Dade-Kotopon Municipal District with a mean index of 2.55 and 2.61 respectively.

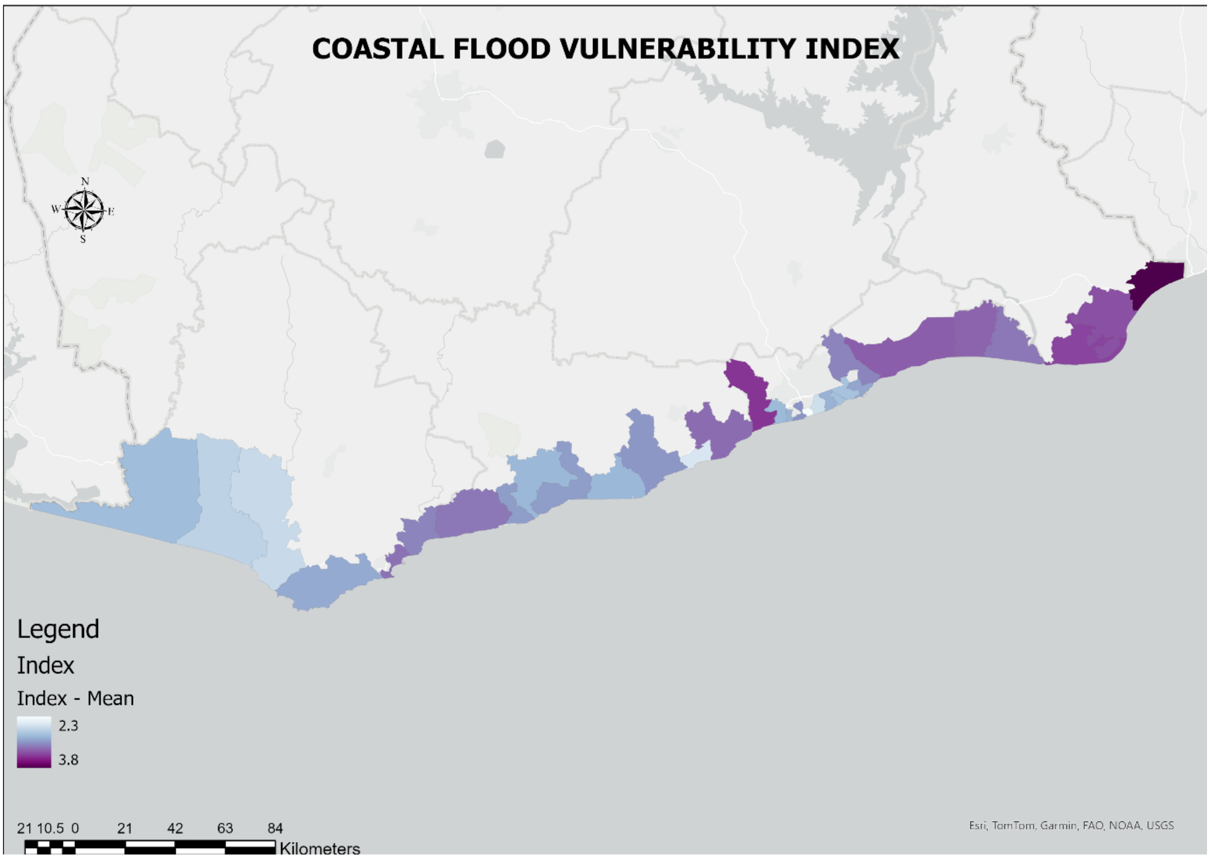

Figure 6: Map of Coastal Flood Vulnerability Index (CFVI)

With regards to the relationship between the PFVI and the FSoVI on the index, both indexes had a positive correlation with the CFVI. However, the FSoVI had a very strong positive Pearsons correlation of 0.90 while the PFVI had a Pearsons correlation of 0.16 indicating a weak positive correlation with the CFVI. The two indexes also have a weak negative correlation to each other with a correlation of -0.29.

Conclusion

This research was conducted using an MCDA-based AHP model approach to assess coastal flood vulnerability in Ghana. The advantage of this method is that it is suitable for analyzing complex decision problems that often involve incomparable criteria or variables (Shahiri Tabarestani & Afzalimehr, 2022). It is also a cost-effective approach to assessing risk and vulnerability to natural hazards (Zou et al., 2013) in a GIS environment which is crucial in a country like Ghana with limited investment in vulnerability research. The AHP also allows the user to structurally compare each variable to the other to understand their relationship before deciding the variable's level of importance (Achillas et al., 2013).

The outcome of the PhyFVI has shown that physically, flood vulnerability is generally moderate to high within the coastal districts of Ghana. With 42 percent of the districts having high physical vulnerability with Ablekuma West Municipal, Accra Metropolitan Area, and Keta Municipal having the highest PhyFVI in the study area. This index is consistent with prior studies conducted in this district as discussed in the findings. Also, the factors behind the high PhyFVI like poor drainage, changing precipitation patterns, drainage density, and many others expanded upon in the findings chapter.

SoFVI on the other hand indicated that only 6.5% of the districts recorded a high SoFVI with Ketu South Municipal recording the highest index. The findings of SoFVI in this district align with prior studies about social flood vulnerability within this district which was also outlined in the prior chapter of this study. The study also revealed that the variable average household size had the strongest correlation with the index.

Finally, after combining both indexes to derive the overall CFVI, Ketu South Municipality was the most vulnerable coastal district to floods within Ghana with an overall index of 3.9 which indicates a high vulnerability to floods. This outcome was supported by the findings of Babanawo et al. (2023) who assessed flood vulnerability within communities of this district. It was also revealed through the correlation of both indexes on the CFVI indicated that the SoFVI had a very strong linear relationship with the index which indicates that SoFVI influenced the outcome of the CFVI that the PhyFVI.

Limitations

This research can inform policymakers in the various coastal districts in Ghana on flood vulnerability and the factors behind it. The strength of this research is that it combines both the physical and social variables to assess flood vulnerability using the MCDA-based AHP model approach (Saaty, 1980) aggregated at a district level using the indicator approach. However, other scholars (Prama et al., 2020) have called for a more detailed assessment using hydrological flood modelling calibrated to the study area for a more detailed assessment of physical vulnerability. The indicator approach used for social flood vulnerability can be improved by using the latest socio-demographic datasets which at the time of the research was unavailable for the last two years in Ghana. Another limitation of our AHP model is that the pairwise comparison was done based on what the author deemed more important when comparing the variables in the model.

Recommendations

For future studies, a hydrological flood model could be used to assess physical flood vulnerability of which the findings could be tested against the indicator-based physical vulnerability approach to see if there is a relationship between the two modelling approaches. In all, this model could be used by the government of Ghana and the various District Assemblies, NGOs, and other agencies in effective monitoring and mitigation strategies when it comes to flooding the coastal districts of Ghana.

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Appendix

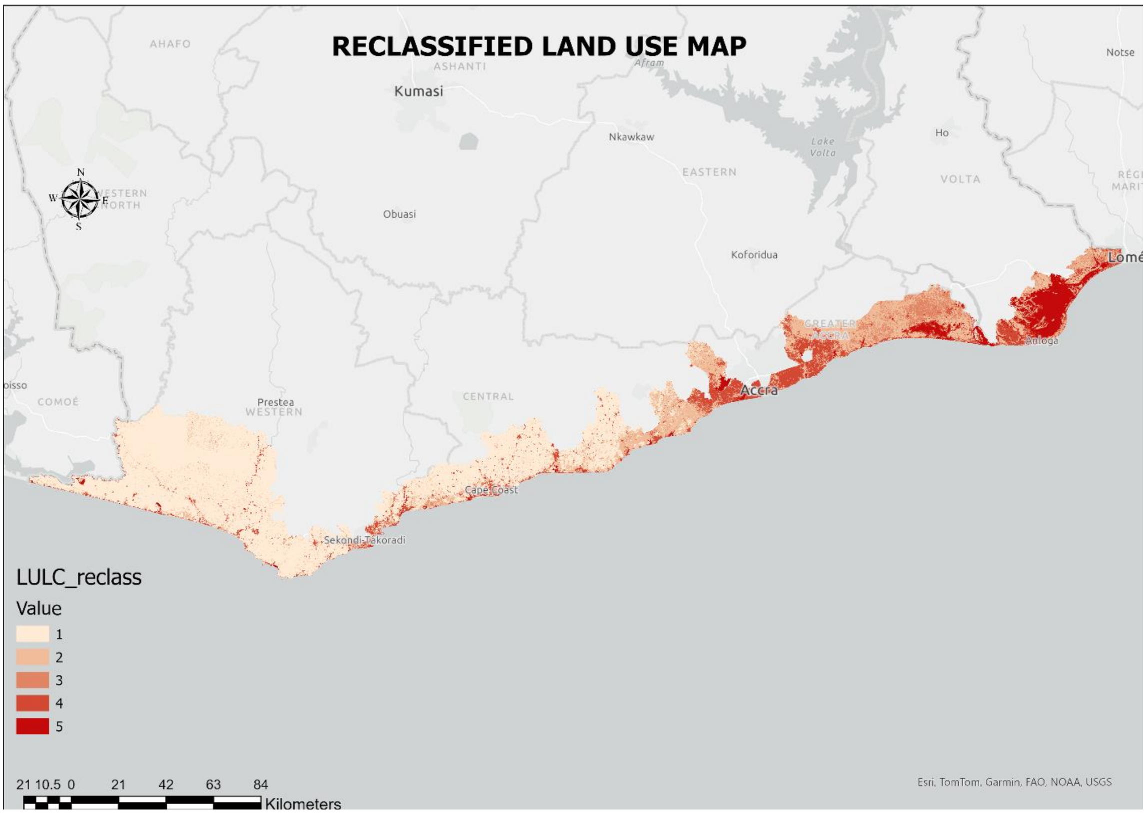

Figure 7: Reclassified Landuse map

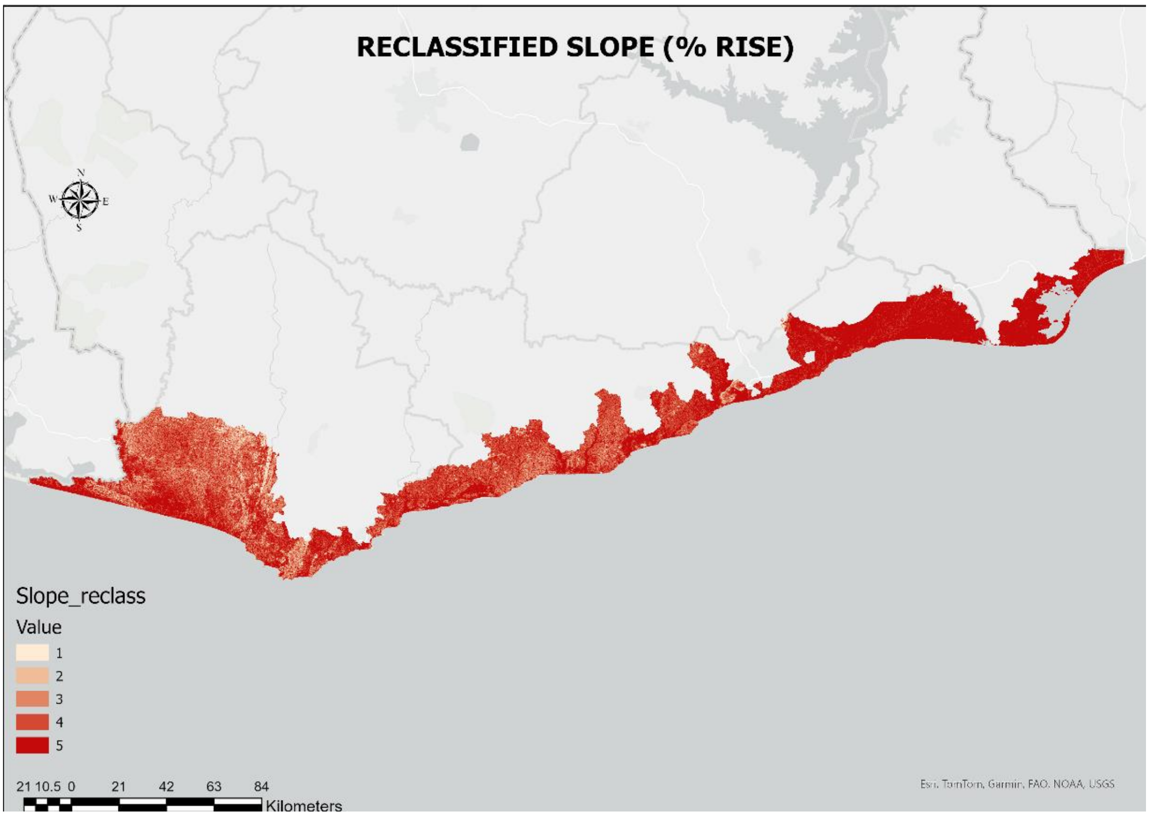

Figure 8: Reclassified Slope map

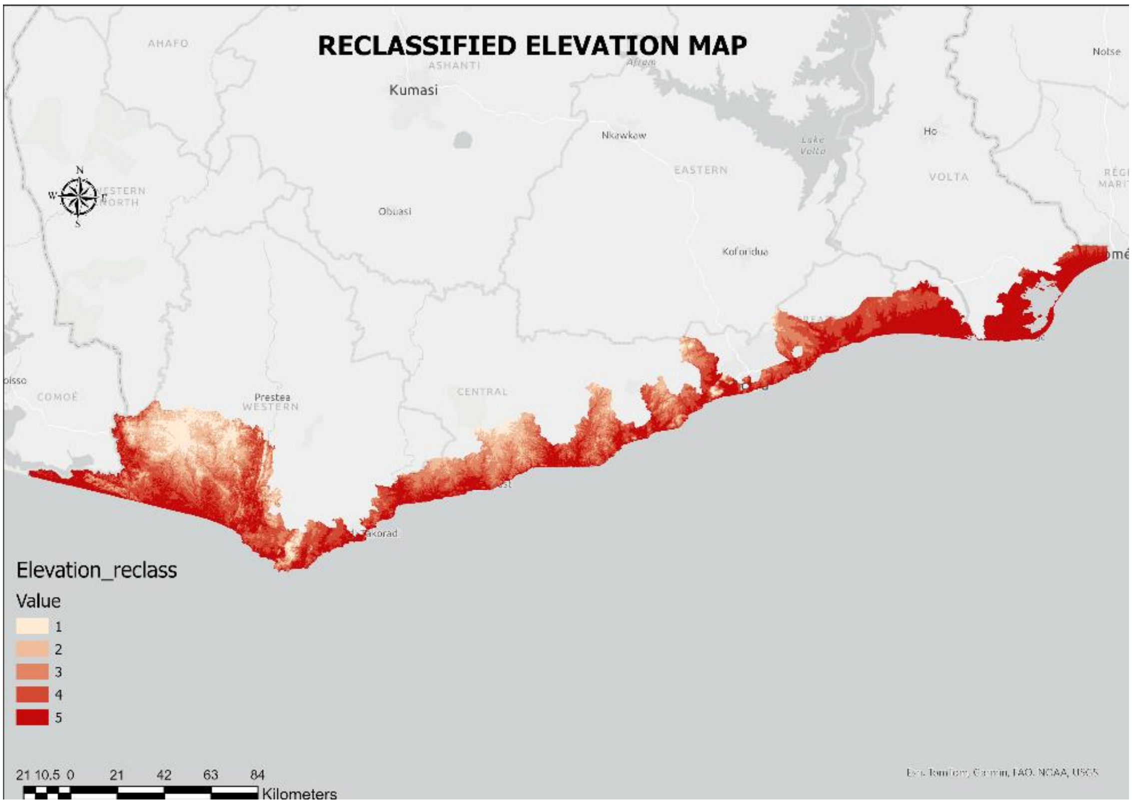

Figure 9: Reclassified Elevation Map

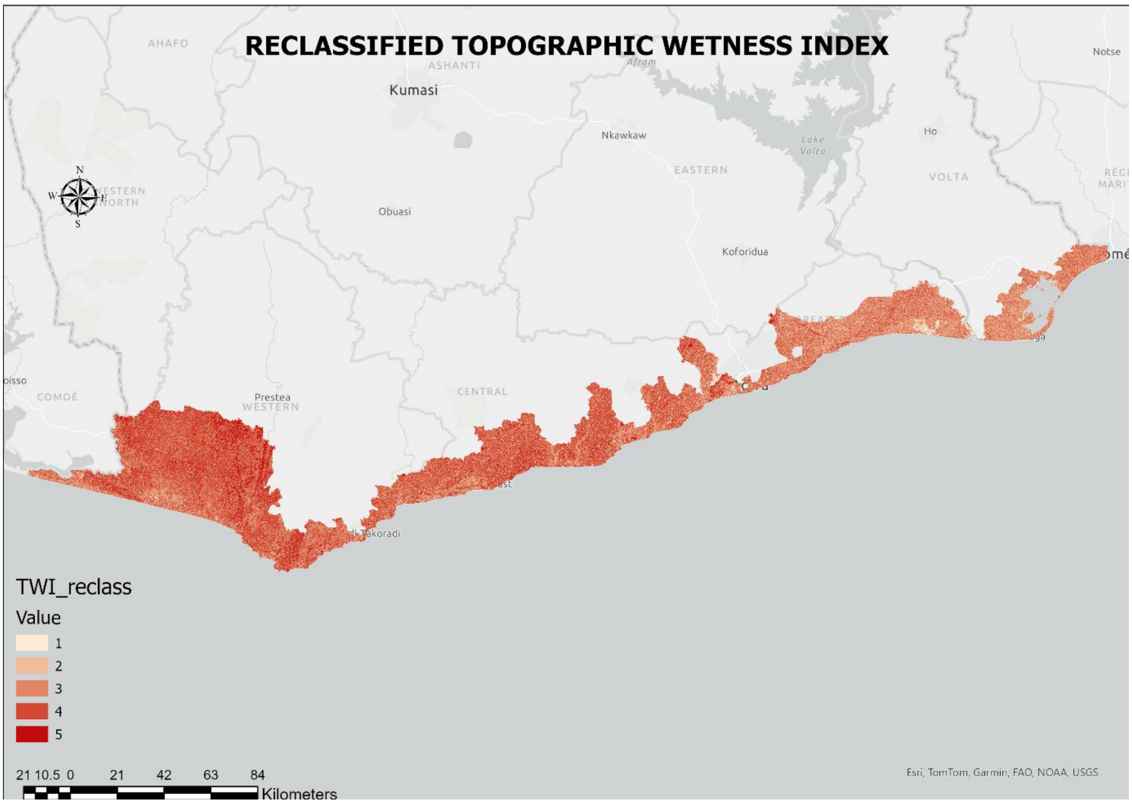

Figure 10: Reclassified Topographic Wetness Index Map

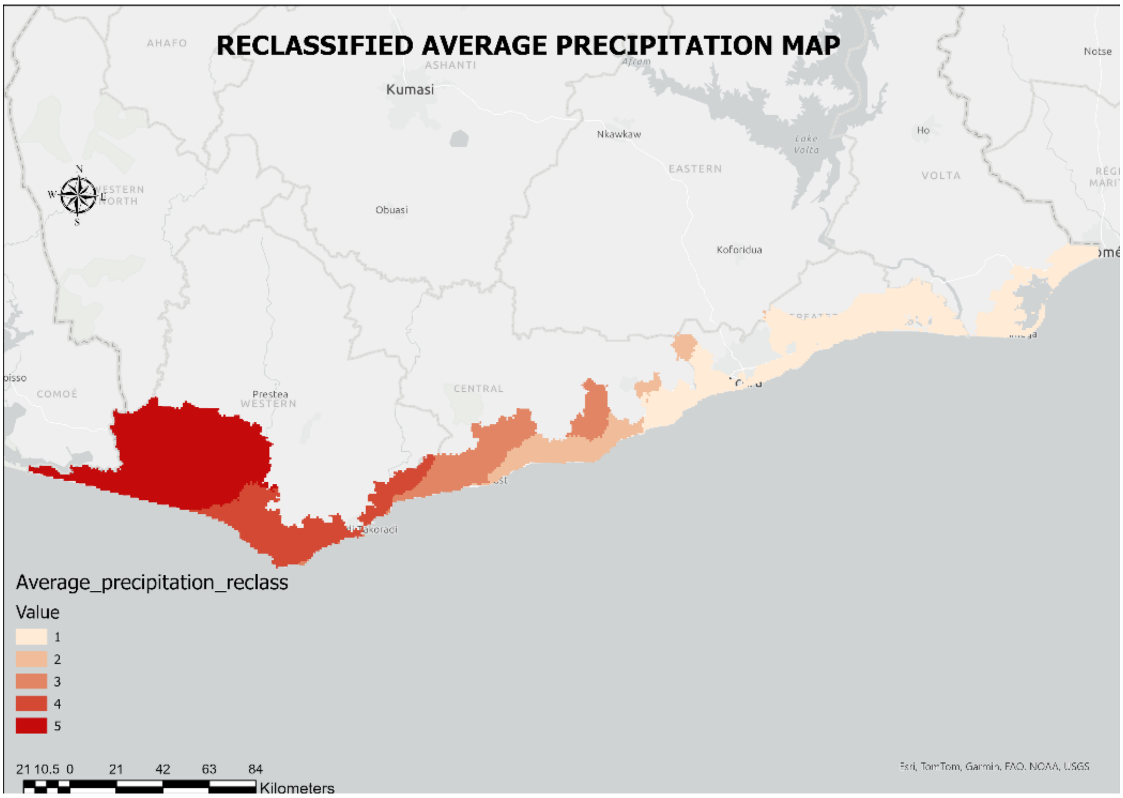

Figure 11: Reclassified Average Precipitation Map

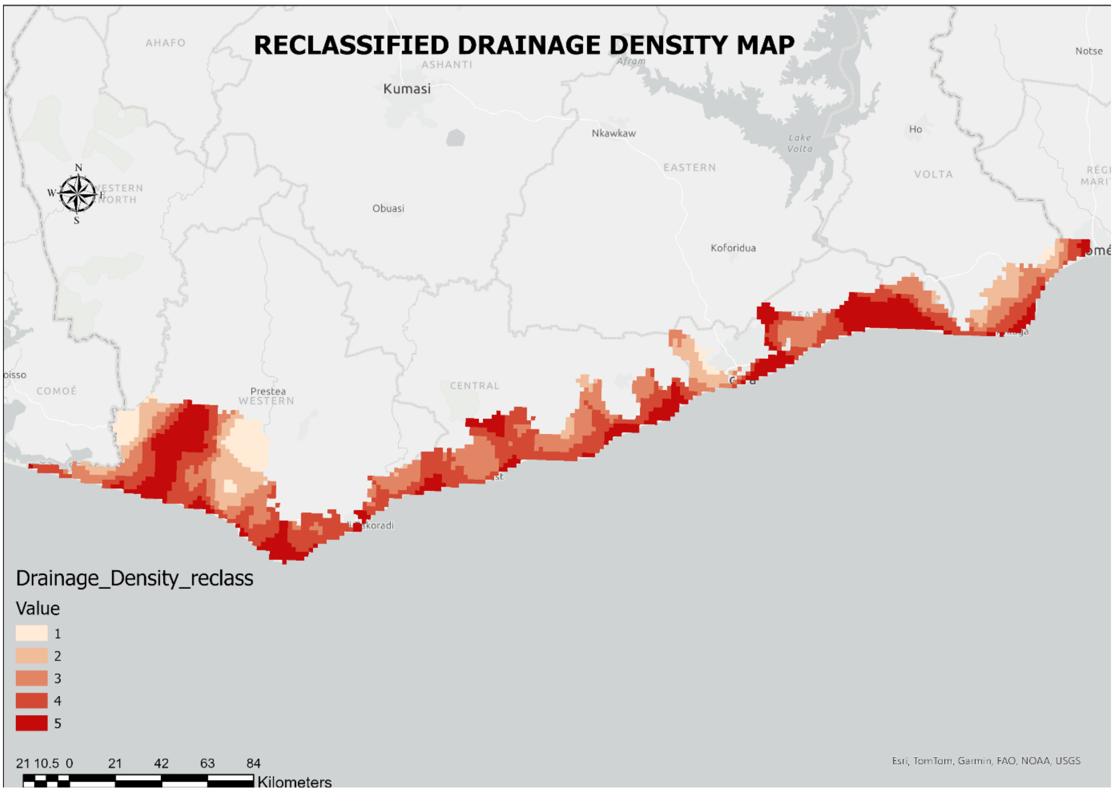

Figure 12: Reclassifed Drainage Density Map

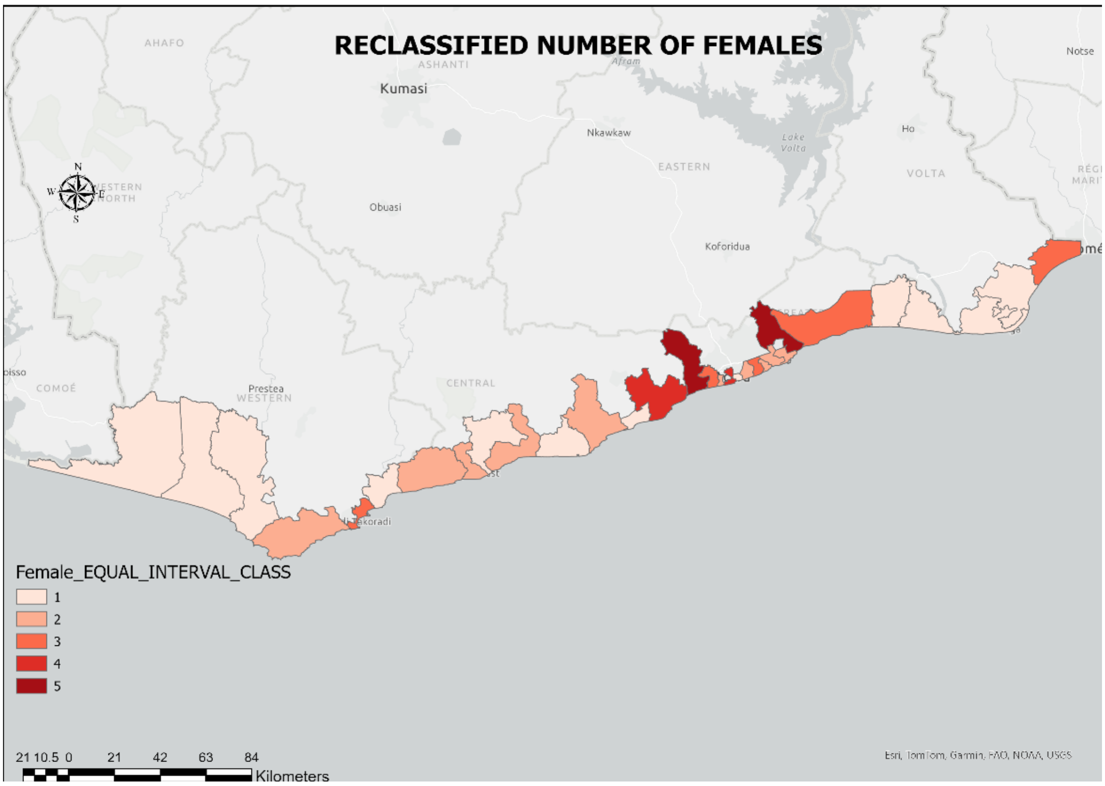

Figure 13: Reclassified Number of Females Map

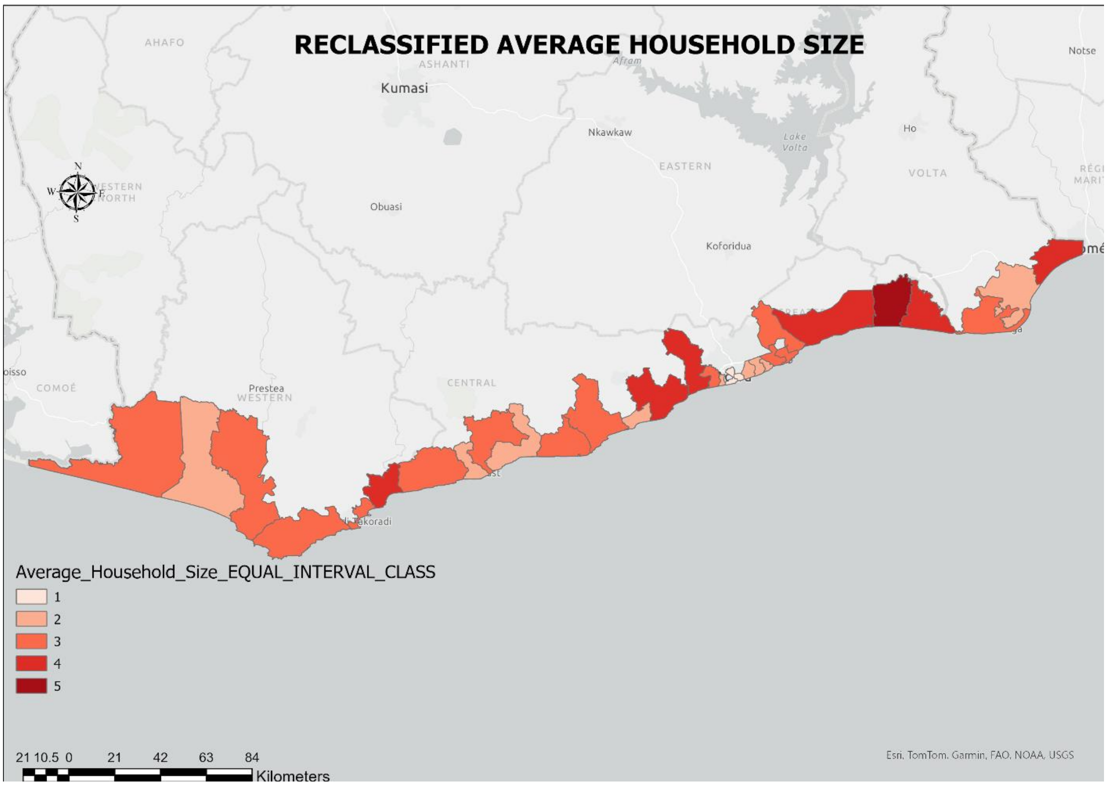

Figure 14: Reclassified Average Household Size Map

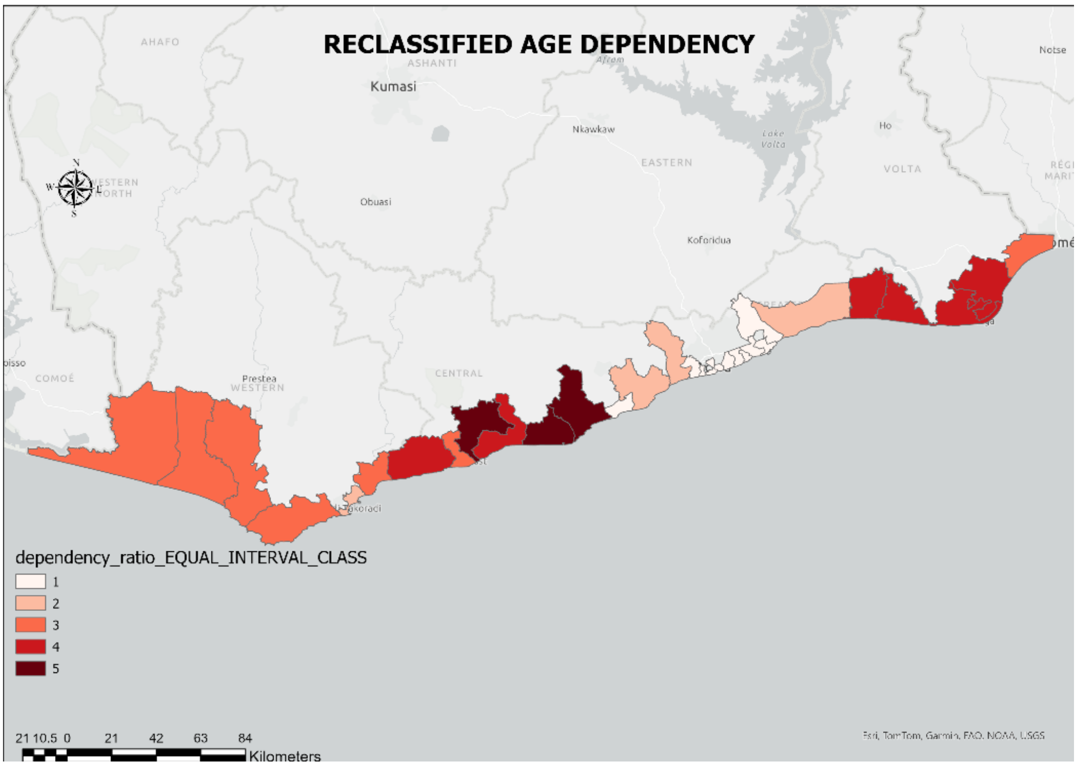

Figure 15: Reclassified Age Dependency Map

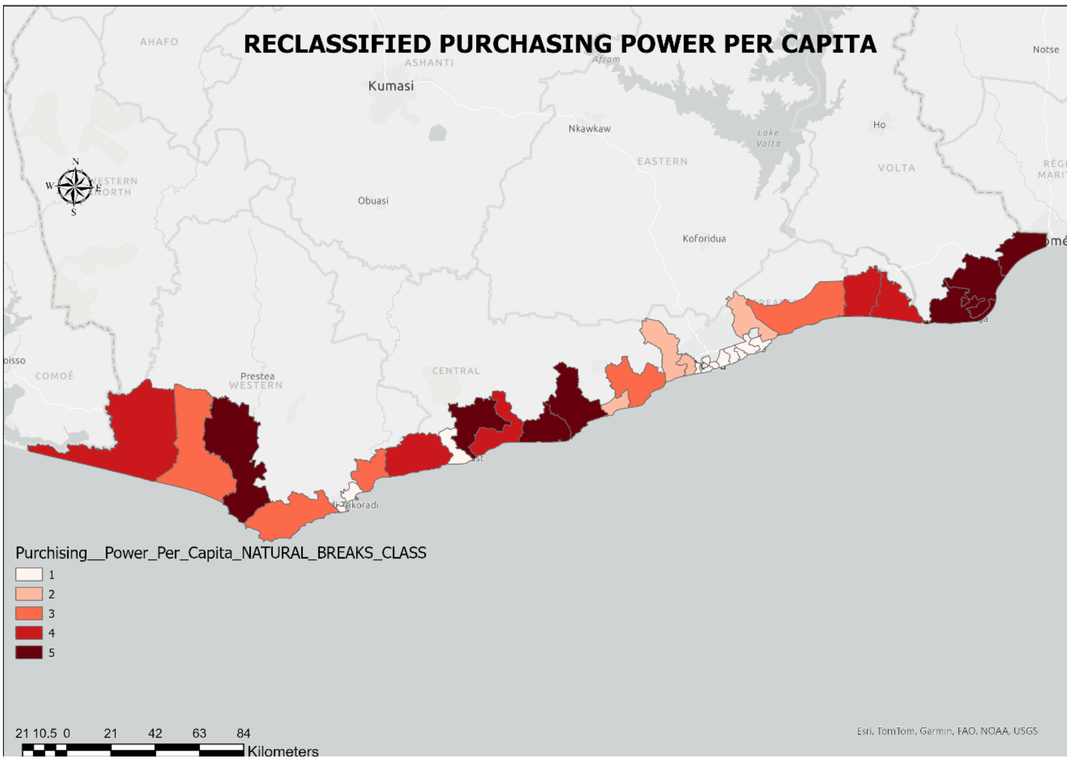

Figure 16: Reclassified Purchasing Power Per Capita Map

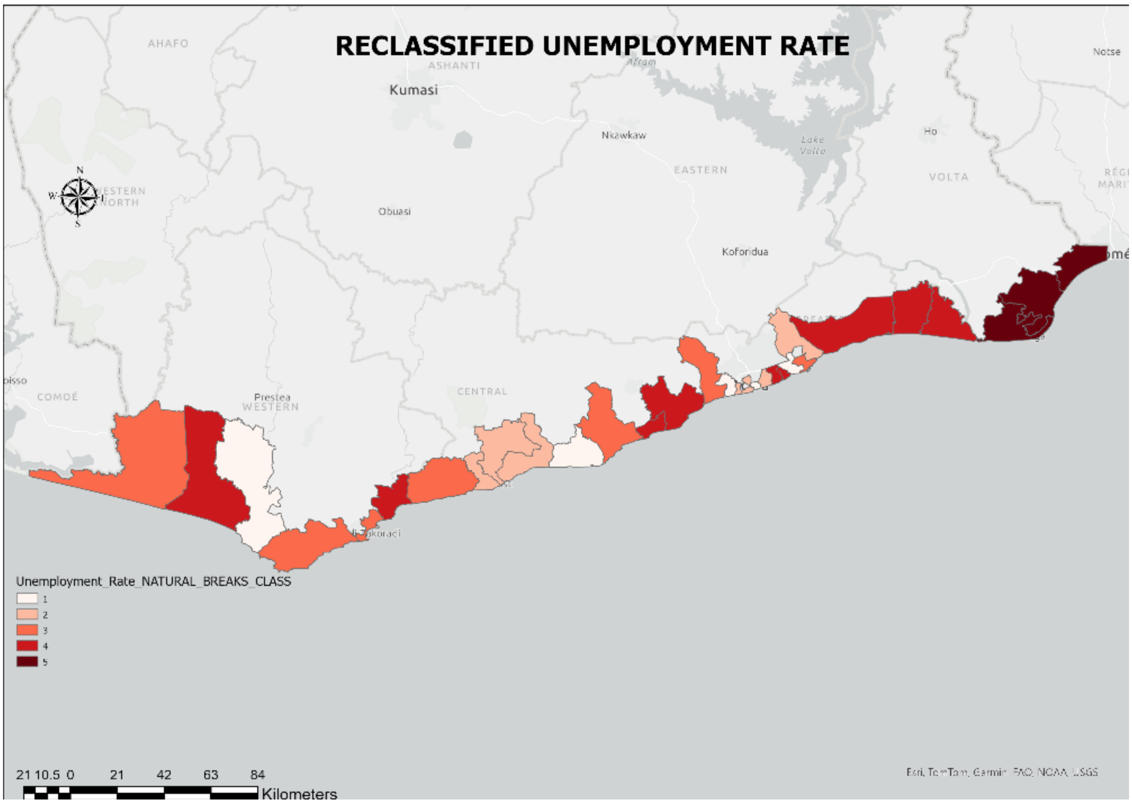

Figure 17: Reclassified Unemployment Rate Map

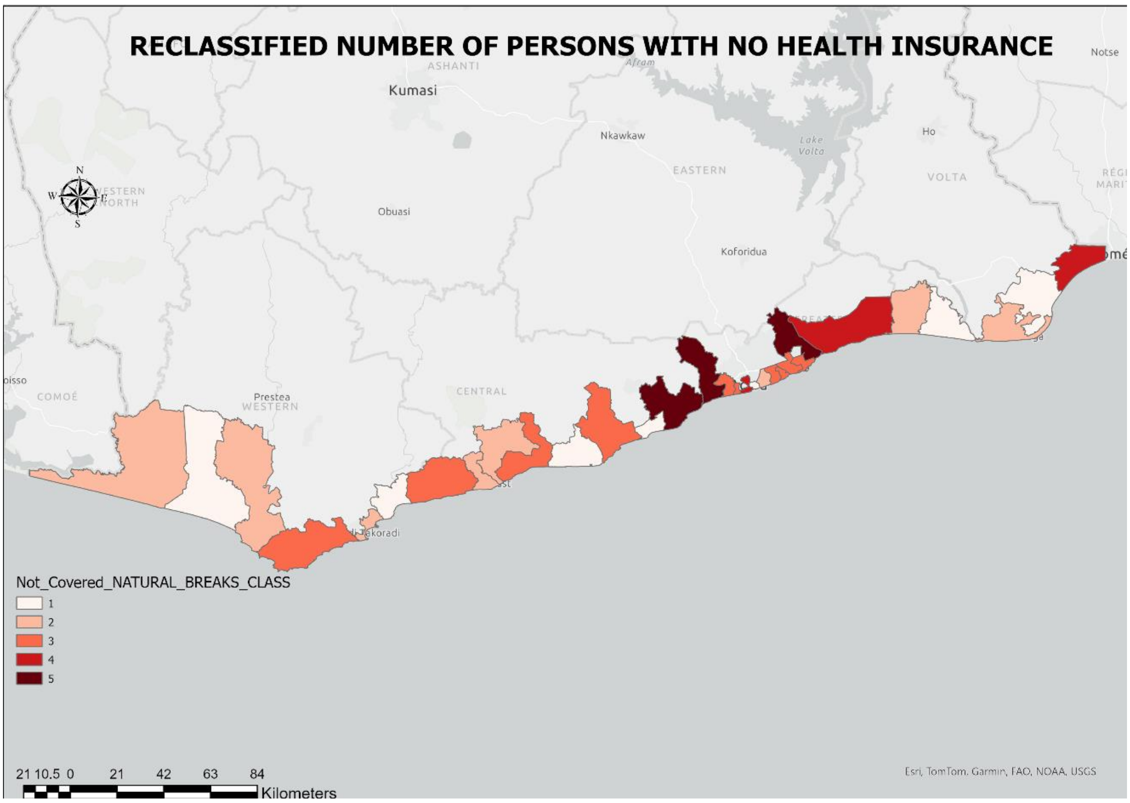

Figure 18: Reclassified Number of Persons with No Health Insurance Coverage Map

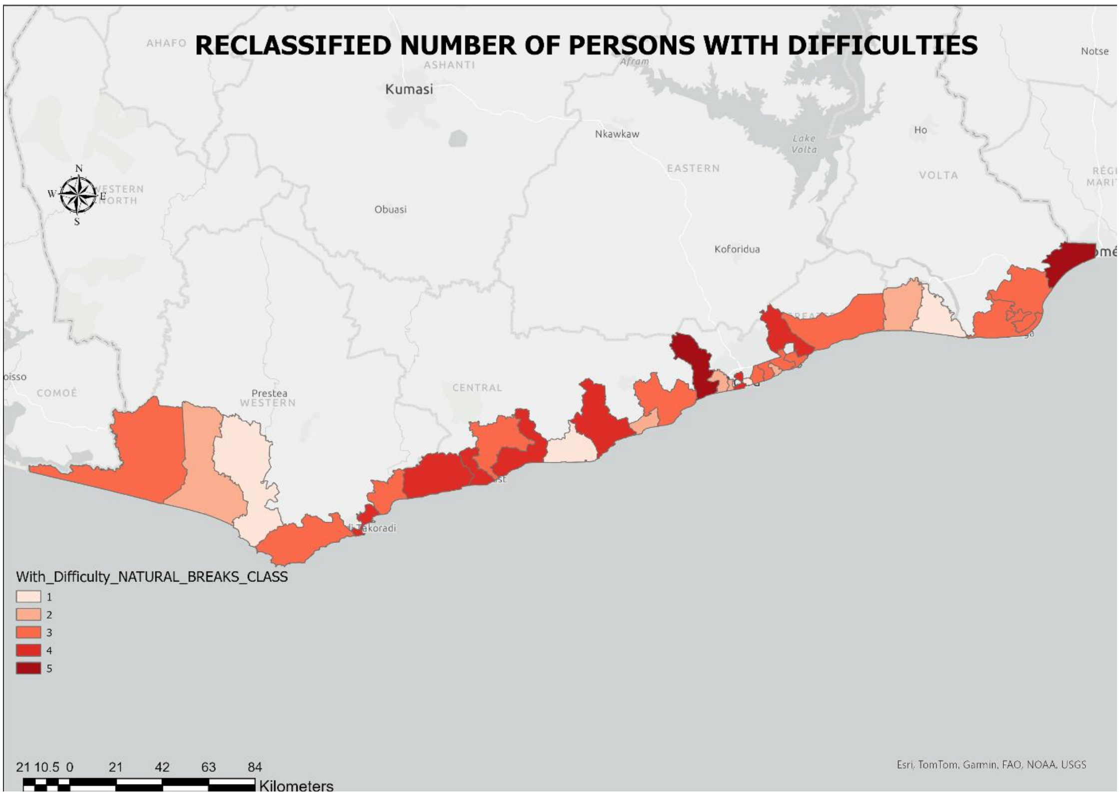

Figure 19: Reclassified Number of Persons With Physical Disabilities Map

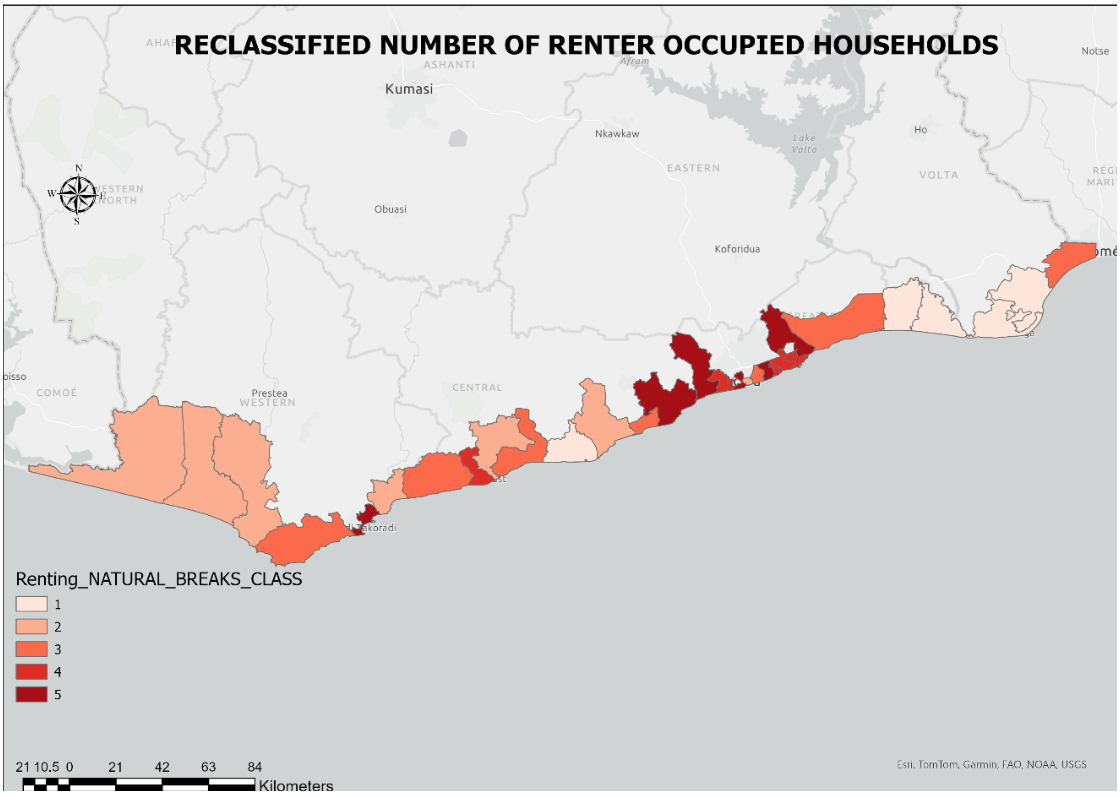

Figure 20: Reclassified Number of Renter Occupied Households Map

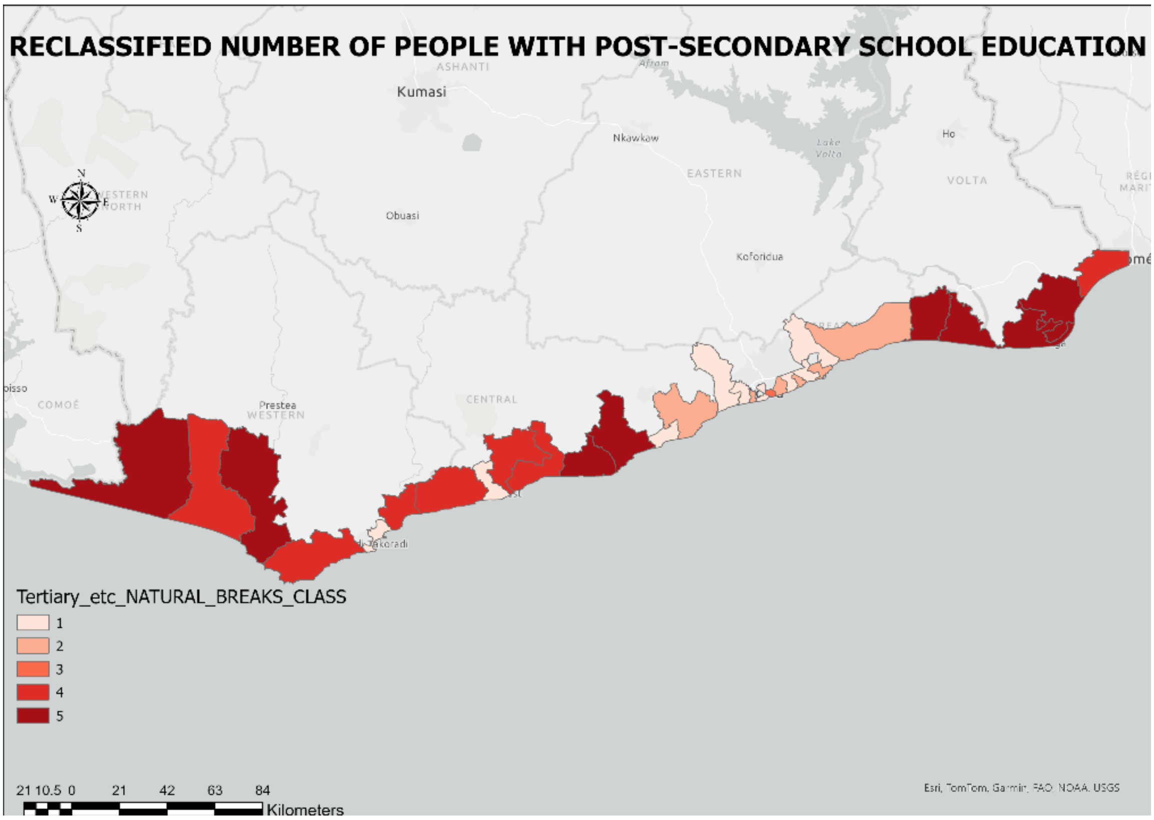

Figure 21: Reclassified Number of People with Post-Secondary School Education Map

Data	Description
Elevation	Name: Void-filled Digital Elevation Model of Africa Source: HydroSHEDS Date: 2008 Datatype: Raster (GeoTIFF) Resolution: 3 arc-seconds Coordinate System: WGS84 Link: https://data.hydrosheds.org/file/hydrosheds-v1-dem/af_dem_3s.zip
Slope	Name: Slope Source: Author Date: 2024 Datatype: Raster Resolution: 3 arc-seconds Coordinate System: WGS84 Measurement: Percent rise
Districts	Name: Ghana Districts Source: Ghana Statistical Service Date: 2021 Datatype: Vector (.SHP) Geometry: Polygon Coordinate System: WGS84 Link: https://statsbank.statsghana.gov.gh/assets/geofiles.zip
Census Data	Name: Population and Housing Census 2021 Source: Ghana Statistical Service Date: 2021 Datatype: CSV Link: https://statsbank.statsghana.gov.gh/pxweb/en/PHC%202021%20StatsBank/
Purchasing Power Per Capita Data	Name: Purchasing Power Per Capita in Ghana Source: ESRI Demographics Date: 2023 Datatype: Web Map Currency: Ghana Cedis Link: https://hub.arcgis.com/maps/esri::purchasing-power-per-capita-in-ghana/explore?location=5.656897%2C-0.270050%2C9.06
Precipitation	Name: Precipitation Source: WorldClim Date: 2020 Datatype: Raster (GeoTIFF) Resolution: 30 arc-seconds Coordinate System: WGS84 Link: https://biogeo.ucdavis.edu/data/worldclim/v2.1/base/wc2.1_30s_prec.zip
Landuse	Name: WorldCover V2 Source: European Space Agency (ESA) Date: 2021 Datatype: Raster (GeoTIFF) Resolution: 10m Link: https://viewer.esa-worldcover.org/worldcover/?language=en&bbox=-337.5,-85.63546635050855,337.5,85.63546635050855&overlay=false&bgLayer=OSM&date=2024-05-21&layer=WORLDCOVER_2021_MAP
Topographic Wetness Index (TWI)	Name: TWI Source: Author Date: 2024 Datatype: Raster (GeoTIFF) Resolution: 3 arc-seconds Coordinate System: WGS84
Drainage Density	Name: Drainage Density Source: Author Date: 2024 Datatype: Raster (GeoTIFF) Resolution: 3 arc-seconds Coordinate System: WGS84

Table 7 Datasets used in this research.

Variable	Reclassification	Remark
Landuse	Tree cover – 1	Lowest
	Shrubland, Grassland – 2	Low
	Cropland – 3	Moderate
	Mangroves, Built-up, Bareland – 4	High
	Permanent Water, Herbaceous Wetland – 5	Highest
Slope	0%-10% - 5	Highest
	10%-20% - 4	High
	20%-30% - 3	Moderate
	30%-40% - 2	Low
	40%+ - 1	Lowest
Elevation (m)	-28 to19.2 – 5	Highest
	19.2 to 43.6 – 4	High
	43.6 to 72.2 – 3	Moderate
	72.2 to 105.1– 2	Low
	105.1 to 337 – 1	Lowest
Topographic Wetness Index	-6.5 to -3.9 – 1	Lowest
	-3.9 to -2.8 – 2	Low
	-2.8 to -1.5 – 3	Moderate
	-1.5 to 0.3 – 4	High
	0.3 to 6.1 – 5	Highest
Average Precipitation (mm)	67 to 90 – 1	Lowest
	90 to 105 – 2	Low
	105 to 122 – 3	Moderate
	122 to 142 – 4	High
	142 to 165 – 5	Highest
Drainage Density (km^2)	1.5 to 4.9 – 5	Highest
	4.9 to 7.2 – 4	High
	7.2 to 9.8 – 3	Moderate
	9.8 to 13.1 – 2	Low
	13.1 to 18.0 - 1	Lowest

Table 8 Reclassification table of physical flood vulnerability variables

Variable	Reclassification	Remark
Number of Females	1 = 30357 to 65707	Lowest
	2 = 65708 to101057	Low
	3 = 101058 to 136406	Moderate
	4 = 136407 to 171756	High
	5 = 171757 to 207106	Highest
Average Household Size	1 = 2.50 to 2.82	Lowest
	2 = 2.82 to 3.14	Low
	3 = 3.14 to 3.46	Moderate
	4 = 3.46 to 3.78	High
	5 = 3.78 to 4.10	Highest
Age Dependency Ratio	5= 110.191717 to 124.230752	Highest
	4= 96.152681 to 110.191716	High
	3= 82.113644 to 96.152680	Moderate
	2= 68.074608 to 82.113643	Low
	1= 54.035571 to 68.074607	Lowest
Purchasing Power Per Capita	5= 9459 to 12061	Highest
	4= 12062 to 13779	High
	3= 13780 to 16308	Moderate
	2= 16309 to 21801	Low
	1= 21802 to 27764	Lowest
Unemployment Rate	1= 10.400000 to 11.200000	Lowest
	2= 11.200001 to 12.600000	Low
	3= 12.600001 to 14.300000	Moderate
	4= 14.300001 to 16.900000	High
	5= 16.900001 to 19.700000	Highest
No Health Insurance Coverage	1= 21523 to 36622	Lowest
	2= 36623 to 51992	Low
	3= 51993 to 84797	Moderate
	4= 84798 to 121139	High
	5= 121140 to 179053	Highest

variable	Reclassification	Remark
Persons with Physical Disabilities	1= 5214 to 6374	Lowest
	2= 6375 to 8799	Low
	3= 8800 to 13446	Moderate
	4= 13447 to 18368	High
	5= 18369 to 23755	Highest
Renter Occupancy	1= 3344 to 5261	Lowest
	2= 5262 to 10537	Low
	3= 10538 to 20239	Moderate
	4= 20240 to 29705	High
	5= 29706 to 51358	Highest
Post Secondary School Education	1= 51971 to 85400	Lowest
	2= 21953 to 51970	Low
	3= 17889 to 21952	Moderate
	4= 10573 to 17888	High
	5= 3560 to 10572	Highest

Table 9 Reclassification table of social flood vulnerability variables