



Measuring vulnerability to assess households resilience to flood risks in Karonga district, Malawi

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Abstract

Many parts of Malawi are prone to natural hazards with varying degrees of risk and vulnerability. This study aimed at obtaining baseline data for quantifying vulnerability of the households to flood risks in Karonga District in northern Malawi, specifically in Group Village Headman Matani Mwakasangila of Traditional Authority Kilupula. The study used cross-sectional survey, and data were collected using a structured questionnaire. This study applied Flood Vulnerability Index and statistical methods to quantify and analyse vulnerability of households in the aspects of exposure, susceptibility and resilience characteristics. Proportional Odds Model also known as Ordered Logistic Regression was used to identify factors that determine vulnerability of households to flood risks. The results show that households headed by females and elders of age (at least 61 years) were the most vulnerable to floods because of their limited social and livelihood capacities, resulting from being uneconomically active group. Households with houses built of mud, thatched and very old with no protective account for high vulnerability due to the fact that most of them are constructed using substandard materials. The level of vulnerability was increasing with an increase in the number of households exposed and susceptible to floods. With an increase in resilience to floods, vulnerability level was decreasing. The results further revealed a predictive margins of vulnerability levels which were not significantly different among the villages. However, villages with more exposed, susceptible and not resilience households were most vulnerable to floods. This study recommends that vulnerability assessment should be included in Disaster Risk Reduction planning and implementation in order to make DRR more efficient and realistic. This would further strengthen the disaster risk management to be more proactive as well as increase resilience of households to flood risks.

Keywords Vulnerability · Floods · Disaster risk reduction · Disaster risk · Karonga · Malawi

1 Introduction

Vulnerability is a component of risk (Nazeer et al. 2020). Its interaction with natural hazard like floods is likely to turn the hazard into a disaster (Birkmann, 2006). Therefore, vulnerability assessment is a step towards development of proper disaster risk reduction (Munyani et al. 2019; Nasiri et al. 2016; Nazeer et al. 2020). Disaster Risk Reduction (DRR) is a concept that every nation considers in order to mitigate issues related to disasters. While disaster stakeholders utilize different measures to reduce disaster risks, measuring vulnerability could be another option to apply (Munyani et al. 2019). Assessing levels of vulnerability assist to identify new DRR strategies towards achieving disaster resilient society (Nazeer et al. 2019; Munyani et al. 2019). Though majority of households particularly in rural areas of Malawi are affected by floods almost every year, but their levels of vulnerability have been not comprehensively measured (Mwalwimba 2020). Different households in different areas experience different levels of impacts under the same magnitude of hazards. This is so because of difference in vulnerability levels to that particular hazard (Barret et al. 2021). Despite the DRR frameworks that recognize how households' vulnerability contributes to an extent of disaster risks, many studies have been conducted to assess natural hazards such as floods and the impacts in Malawi without quantifying the level of vulnerability. Several interventions also have been done in African countries including Malawi with the aim of minimizing the probabilities of negative impacts that people and any other exposed elements tend to encounter before, during and after the occurrence of a particular hazard. While every country needs to improve the livelihoods of her citizens, there is a need to analyse households' vulnerability to natural hazards to adopt an appropriate, sustainable, effective and efficient approach of mitigating natural disaster risks (Mwalwimba 2020).

In Malawi, there have been many efforts done by Government, Civil Society Organisation, Local and International Organisations with the aim of mitigating flood disaster risks. Risk Reduction Frameworks, Policies and Acts have been developed but still majority of people in Malawi; precisely in communities are victims of floods. The National Disaster Recovery Framework (NDRF) Policies that was developed in 2015, puts emphasis on decentralization approach (from village to national level) and community participation in mitigating flood risks. However, for all these approaches to be effective there is a need to understand disaster risk because of the interaction between hazard and vulnerability. There is a mention that while it is not easy to stop floods, but vulnerability of people to flood disaster is manageable. Yet all start by finding out how vulnerable the people are in the areas in relation to exposure, susceptibility and resilience to floods. However, while studies done in Malawi have attempted to quantify and analyse vulnerability in the aspects of exposure, susceptibility and resilience (Adeloye et al. 2015), the application of statistical approaches, which could mark as a basis for providing indicators to support decision making process. This could further help to provide data necessary for the participation of the community towards the mitigation of disaster risks. Therefore, this study was designed with the aim of forming a basis of quantifying and analysing vulnerability of households through the understanding of household exposure, susceptibility and resilience to flood risks.

2 Study methodology

2.1 Study design

This study was based on a cross-sectional sample survey of households using structured household questionnaire survey. Flood vulnerability components (exposure, susceptibility

and resilience) linked with demographics (age, sex, marital status, education and occupation) were variables selected in this study. The components were constituted in equation $FVI = (E * S) \div R$ or $(E * S) - R$ where E is exposure, S susceptibility, R is resilience and FVI is Flood Vulnerability Index (Munyani et al. 2019).

2.2 Study location

Malawi is a landlocked country in Central Southeastern Africa. It has been ranked 170 out of 188 nations and territories in the category of low human development with HDI value of 0.476 (UNDP 2016). Over 65% of Malawians live on less than \$1 a day (FEMA, 2018). The situation in Malawi illustrates the drastic increase of the frequency and magnitude of disasters caused by natural hazards. For example, since 1946, Malawi has been hit 298 times by hazards of which 89% have been natural hazards and 11% have been human-generated events (DoDMA 2014).

Specifically, this study targeted GVH Matani is the Northeastern part of Karonga district in Traditional Authority Kilupula (Fig. 1). The topography and geology of district ranges from 400 m at the lake shore to 2400 m at the high Nyika Plateau. It is predominantly hilly, especially west of Lake Malawi. Most outstanding landforms can be divided into three zones: (a) the High Hills and Plateau, (b) the Rift Valley Escarpment and (c) the Lake shore Plain. Due to the many different types of sediments and rocks a wide variety of soils have developed in Karonga District that varies from area to area. Different kinds of soils according to area existing are weathered ferralitic soils/lithosols, lithosols and undifferentiated lithosols, alluvial soils, often calcimorphic soils and gleys (KSEP, 2013).

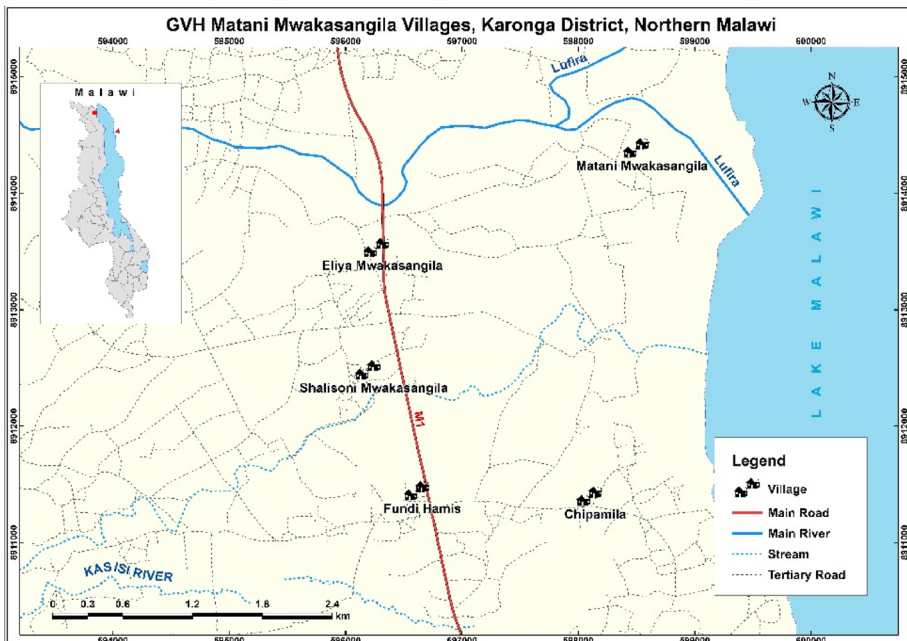


Fig. 1 Map of traditional authority Kilupula showing location of villages

The study was done in this GVH for a number of reasons. The area of T/A Kilupula is among the areas that majority of households get affected by flood disasters (Kamanga et al. 2020). For instance, based on the flood assessment carried out in 2016 by Karonga District Civil Protection Committee (DCPC), 1573 houses were destroyed, and 5325 were damaged from 2010 to 2016 due to flood disasters. There are also countless cases of livestock losses and disruption of services such as education, markets and others that would sustain the livelihood of people. Majority of people in GVH Matani sorely depend on agriculture and fishing for their living. These are the sectors that are also most likely to be affected by flood hence create a zone where people cannot easily adapt, cope with and recover from the impact after flood disasters. Therefore, it was found necessary to analyse their vulnerability to floods basically to measure their exposure, susceptibility and resilience to flood disasters.

2.3 Data collection

This study used a household questionnaire survey to collect data from the households located in the villages closer to the river and lower elevation thresholds were of targets of the study. Five Villages in GVH Matani namely Shalisoni, Eliya, Matani, Fundi and Chipamila in Group Village Headman (GVH) Matani Mwakasangila were targeted. Household participants were selected using simple random sampling. Data were collected using structured questionnaire that was also translated in the local vernacular Ngonde language to be easily understood by the respondents. This study used 100 of the questionnaires collected in GVH Matani to analyse and quantify vulnerability.

A total of 100 households' participants were used. This sample size was determined based on Fisher et al. (2010) formula $n = \frac{z^2 pq}{d^2}$, which consider the power of precision ($d=0.05$) and a proportional of target population (P) as a percentage of the of number of population and the confidence level ($Z=1.96$ for 95%).

2.4 Indicators of flood vulnerability

The indicators were normalized such that their values ranged from 0 to 1. Normalization was based on assumptions that vulnerability is positive with positive exposure and susceptibility indicators and it decreases with an increase in resilience. Normalization and weighting was adapted from Balica et al. (2012). This quantification aimed to come up with Flood Vulnerability Index that was used to compare flood vulnerability of different households in the flood prone area. Normalization depends on a relationship between exposure, susceptibility resilience and household vulnerability. Vulnerability increases with an increase in exposure and susceptibility, and it decreases with an increase in Resilience, according to Iyenger, 1982. Test for normality was done on a normalized data after being quantified.

Therefore, indicators that were from the exposure and susceptibility components of vulnerability were normalized by (Nazieer et al. 2020):

$$Y_{ij} = \frac{x_{ij} - \text{Min}\{x_{ij}\}}{\text{Max}\{x_{ij}\} - \text{Min}\{x_{ij}\}} \quad (1)$$

where Y_{ij} is a standardized score for x_{ij} exposure and susceptibility indicators.

$\text{Max}\{x_{ij}\}$ and $\text{Min}\{x_{ij}\}$ are the maximum and minimum scales respectively for x_{ij} indicator of a particular component of vulnerability.

In case of an indicator from resilience component, values were normalized by

$$Y_{ij} = \frac{\text{Max}\{x_{ij}\} - x_{ij}}{\text{Max}\{x_{ij}\} - \text{Min}\{x_{ij}\}} \tag{2}$$

The normalized values were weighted to ensure that large variation in any of the indicators were not unduly dominating the contribution of the rest of the indicators and that of the households. This kind of weighting ensured the homogeneity of variance that helped during vulnerability analysis.

The weighting was done using the formula as follows:

$$W_{ij} = \frac{k}{\sqrt{\text{var}(x_{ij})}} \tag{3}$$

where k is a normalizing constant, defined as

$$k = \left[\frac{1}{\sum_{j=1}^c \left(\frac{1}{\sqrt{\text{var}(x_{ij})}} \right)} \right] \tag{4}$$

where c is a total number of indicators in a particular vulnerability component.

Therefore, the weighted value for a particular indicator of a particular vulnerability component was given by;

$$G_{ij} = W_i Y_{ij} \tag{5}$$

Composite Vulnerability Index was produced by adding the weighted values of indicators of particular vulnerability component per particular household.

$$M_{vc} = \sum_{j=1}^c \frac{W_i Y_{ij}}{c} \tag{6}$$

where M_{vc} represent an exposure index, Susceptibility index, and Resilience index of a household, and c was the number of variables measured in a particular component of vulnerability at household level.

Flood vulnerability index per household was calculated from the composite vulnerability index as follows:

$$\text{FVI} = f(E_i, S_i, R_i) \tag{7}$$

where E_i be an exposure index, S_i is a susceptibility index and R_i is a resilience index.

All these were done in STATA version 12. The score of vulnerability was determined by the flood vulnerability index of a particular household. Since FVI of a household was ranging from 0 to 1, then those with value from 0 to less than 0.35 were considered less vulnerable, those with index ranges from 0.35 to less than 0.7 were considered more vulnerable and those with at least 0.7 were considered most vulnerable to flood disasters.

Table 1 Response and demographics

Variable	Vulnerability factors	Level of measurement
Response	Vulnerability	0 = vulnerable; 1 = more vulnerable; 2 = most vulnerable
Demographic	Age	0 = 20–40 years; 1 = 40–60 years 2 = 61 +
	Marital status	0 = married, 1 = not married
	Education level	0 = no formal; 1 = primary; 2 = secondary
	Occupation	0 = business; 1 = farming; 2 = fishing

Table 2 Vulnerability components

Exposure	Access to main road	0 = No, 1 = Yes
	Altitude	0 = at most 490 m, 1 = greater than 490 m
	Family size	0 = small (<= 6), 1 = big (> 6)
Susceptibility	Surrounded by forest	0 = No, 1 = Yes
	Early warning	0 = No, 1 = Yes
	Disaster training	0 = No, 1 = Yes
	Relief	0 = No, 1 = Yes
Resilience	Prediction method	0 = None, 1 = Radio; 2 = Indigenous knowledge
	House elevated	0 = No, 1 = Yes
	Level house repaired	0 = Not repaired; 1 = nonstandard; 2 = Standard
	Protective wall	0 = No, 1 = Yes
	Evacuation	0 = No, 1 = Yes
	Raising river banks	0 = No, 1 = Yes

2.5 Variables and measurements

This study categorized the variables into response variable and demographics (Table 1) and vulnerability components (Table 2). These variables were selected from the Malawi National Statistics reports and based on a through review of global contemporary frameworks.

2.6 Data analysis

This study analysed data at three levels. Firstly, through univariate analysis. This part of analysis looked at the descriptive statistics of the socio-demographic factors used in this study. It also looked at the frequency of vulnerability per category from a sample of 99 households in GVH Matani, in Karonga district. Both percentages and frequencies were obtained for the levels of vulnerability and the associated socio-demographic factors. Secondly, through bivariate analysis. This section used a chi-square statistics to test the association that exists between the vulnerability of the households and socio-demographic, exposure, susceptibility and resilience factors. The formula for chi-square statistics is:

$$\chi^2 = \sum \frac{(O_{ij} - E_{ij})^2}{E_{ij}} \tag{8}$$

In addition, it follows a χ^2 with $(r - 1)(c - 1)$ degrees of freedom. Where.

- O_{ij} is the observed counts in cell ij ; $i = 1, 2, 3, \dots, r$ and $j = 1, 2, 3, \dots, c$ where r is the number of rows and c is the number of columns in an $r \times c$ contingency table.
- E_{ij} the expected counts in cell ij ; $i = 1, 2, 3, \dots, r$ and $j = 1, 2, 3, \dots, c$ where r is the number of rows and c is the number of columns in an $r \times c$ contingency table.

The strength of an association was also tested and Cramer’s V and phi (φ) coefficient were used.

The formula for φ is:

$$\varphi = \sqrt{\frac{\chi^2}{n}} \tag{9}$$

where χ^2 is the chi-square statistics and n is the total sample size. In this study $n = 99$.

Lastly, through multivariate analysis. The multivariate analysis was to identify the factors that affect the level of households’ vulnerability to flood disasters, and to model the response variable as a function of exposure, susceptibility and resilience using an ordered logistic regression. This used an ordered logistic regression. Ordered logistic regression is a generalization of a binary logistic regression model when the response variable has more than two ordinal categories. It is a commonly used model for the analysis of the ordinal categorical data. It is also called Proportional Odds (PO) Model or Cumulative Odds Model. Proportional Odds model is used to estimate the odds of being at or below a particular level of the response variable. Similarly, it estimates the odds of being at or beyond a particular level of the response variable as well, because below and beyond a particular category are just two complementary directions. The name Proportional Odds Model for an Ordinal logistic regression is emphasizing on an assumption that the model has to satisfy in order for it to be applied.

This assumption is known as *proportional odds assumption*; sometimes it is called parallel line assumption. Proportional odds assumption states that there should be no coefficient variation among levels of a response variable on a particular explanatory variable in the model. The model uses a *logit link* and in STATA, an *ologit* command is used to run a model. Coefficient estimates are known as maximum likelihood estimates MLE, which are usually estimated using maximum likelihood. The maximum-likelihood estimates are computed iteratively.

An ordered logistic model can be written as follows:

$$\text{logit}[p(y \leq j | x_i)] = \alpha_j + \sum_{i=1}^n \beta_i x_i \tag{10}$$

where y is a response variable (vulnerability of households in this study), j is a level of a response variable (0=less vulnerable, 1=more vulnerable, 3=most vulnerable), x_i is an i th explanatory variables, β_i is a coefficient estimate of an i th explanatory variable. This coefficient estimate is the same for each level of a response variable.

This study used *gologit2 Likelihood Ratio (LR) test* to check whether proportional odds assumption was violated or not. This is a post analysis test. Therefore, it can be used after running a regression and acts on the most recent regression. This test works by contrasting a model in which no variables are constrained to meet parallel lines assumptions with a

model in which all variables are constrained to meet the assumption. If the LR chi-square test is significant, at least one of the variables violates the parallel line assumptions. This test was done at significant level of 5%. The command used was *lrtestgologitologit, stats* in STATA version 12.0. The null hypothesis can be rejected if p value is less than or equal to 5%, otherwise it is proved to be true.

2.6.1 Margins and predictions post analysis

Margins and predictions are post analyses that are run soon after a regression model. Margins were applied in this study as the way to predict vulnerability of households among the seven villages in GVH Matani based on any other explanatory variables. The interaction between explanatory variables in the model makes interpretation difficult. However, after fitting the model one can obtain predictive margins for each of the levels in the interaction of explanatory variables. Margins also are used to test if there is a significant difference in the probability of an outcome within a particular categorical independent variable. The probabilities of vulnerability level for a household that was located in a particular village with the considerations of other explanatory factors such as exposure, susceptibility and resilience were predicted and graph were plotted as shown in the results chapter. The probability of an outcome for an ordered response variable can be calculated as follows:

$$P(Y = j) = \frac{1}{1 + \exp(Z - \alpha_j)} \quad (11)$$

where $Z = \sum_{i=1}^n \beta_i x_i$, α_j is the threshold of j th level of a response variable. $\beta_i x_i$ is as described in the ordered logistic model above. The Z part is calculated by the *predict* command in STATA. The command also can be used to predict the probabilities of a response variable under given conditions on a response and explanatory variables.

2.7 Results

2.7.1 Households demographics based on vulnerability components

The results shows that amongst the less vulnerable households, majority (97%) of them sampled in GVH Matani were resilient to flood disasters with 58% susceptible and 2% exposed. Those that were more vulnerable, majority (85%) were susceptible with 76% resilient and 28% were exposed to flood disasters. For those that were most vulnerable majority 98% were susceptible to flood disasters with 85% exposed and 26% resilient. Figure 2 also shows an increase trend of exposure and susceptibility as one change the vulnerability levels from less to most vulnerable. There is a decrease trend of households' resilience with an increase in vulnerability levels (Fig. 1).

The results further revealed that 33 (33.3%) were less vulnerable, 25 (25.3%) were more vulnerable and 41 (41.4%) were most vulnerable to flood disasters in GVH Matani. According to age, the majority of the respondents 44 (44.5%) were those of age at least 61 years, while 24 (34.2%) and 31 (31.3%) were those of belonging to age group of 20–40 years and $41 \geq 60$ years, respectively. Majority of the less vulnerable household 18 (54.5%) were in the age group of $41 \geq 60$ years, and it was the same age group with the majority 12 (48%) who were more vulnerable. Majority of those that were most vulnerable, 40 (97.6%) were respondents of age at least 61 years. Most of the respondents were males 61% and were

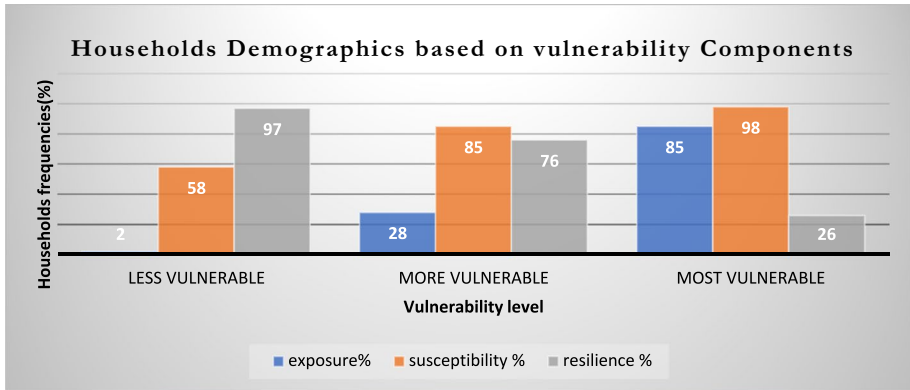


Fig. 2 Households demographics

married 61.6%. The study noted those around 60 years and above find it difficult to rebuild their homes once their houses are damaged by floods. Most of these people live in very weak buildings prone to flooding. Majority of the respondents were primary school leavers 62.6%, and most of the respondent were farmers 56.6%. Most of those that were less and more vulnerable were male with 100% and 88%, respectively. Majority of the most vulnerable respondents were female 85.4%. Basing on how the respondents were able to predict the occurrence of floods, majority 52 (52.5%) were using indigenous knowledge such as observing hill flowers to predict floods occurrence, and with 13 (13.1%) and 34 (34.4%) were using neither and technology such as radio and river gauges respectively. Majority of those that were most vulnerable to flood disasters were using indigenous knowledge 68.3%.

2.7.2 Vulnerability and socio-demographic factors

The results shows that the age group, gender and occupation of the respondents were associated with households’ vulnerability factors. Amongst the significant socio-demographic factors, there was a strong association between vulnerability and the occupation of the respondent, then followed by age group and gender with ϕ values of 1.137, 0.9011 and 0.8176, respectively (Table 3).

2.7.3 Vulnerability and exposure factors

The results of the Chi-square test revealed that vulnerability was associated with access to main road, altitude, and availability of the forest. Based on the values of ϕ , there was a strong association between vulnerability and altitude with $\phi=0.8007$ (Table 4).

2.7.4 Vulnerability and susceptibility factors

The results revealed significant association of all the susceptibility factors with the household’s vulnerability to floods at a 5% significant level. Whether the respondent was trained or not showed strong association with ϕ value of 0.5590 (Table 5).

Table 3 Vulnerability and socio-demographic factors

Component	Factors	Total (%) for vulnerability (whether less, more or most vulnerable)	Chi-square	φ	p -value
Socio-Demographic	Age Group	24	80.3882	0.9011	< 0.001
	20–40	31			
	41–60	44			
	> = 61				
	Gender	61	66.1808	0.8176	< 0.001
	Males	38			
	Females				
	Marital status	88	3.3021	0.1826	0.192
	Married	11			
	Not married				
	Education	22	4.4116	0.2111	0.353
	No formal	62			
	Primary	15			
Secondary					
Occupation	10	127.9929	1.137	< 0.001	
Business	56				
Farming	33				
Fishing					

2.7.5 Vulnerability and resilience factors

Chi-square testing for association between vulnerability shows that all the resilience factors were associated with the households' vulnerability to flood disasters (Table 6).

2.7.6 Factors that affect the households' vulnerability to flood disasters

The results revealed that gender, elevation, house type and protective wall were factors that significantly affect households' vulnerability in the study area. Evacuation, prediction of flood, availability of forest and disaster training were not significant factors of vulnerability in this study (Table 7).

The results also show that females had higher odds of being more and most vulnerable compared to males. The odds of being most vulnerable for a household headed by a female was 32.04 times higher than that of being less and more vulnerable to floods when other factors were kept constant. Elevation measured an altitude where the house of the respondent was located. The results show that the odds of being less vulnerable is 1.23 times higher for a 1 m increase in altitude than that of being more and most vulnerable in GVH Matani. Respondents with strong houses had the odds of 0.06 times less of being most vulnerable than that of being more and less vulnerable. The odds of being most vulnerable for respondent with a very strong houses was 98% times less compared to that odds of being less and more vulnerable. Finally, the odds of being most vulnerable in GVH Matani for respondents that protected the wall of their houses was 83% times less than of being most and less vulnerable (Table 6).

Table 4 Vulnerability and exposure factors

Exposure		Chi-square	φ	p -value
<i>Accessibility to main road</i>				
Accessible	43	7.3127	0.2717	0.026
Not accessible	56			
<i>Altitude(m)</i>				
< =490	39	63.4737	0.8007	<0.001
> 490	60			
<i>Family size</i>				
Small (<=4)	26	0.7913	0.08940	0.673*
Big (>4)	73			
<i>House type</i>				
Weak	37	47.2137	0.0672	<0.001
Strong	62			
<i>Forest Destroyed</i>				
Not destroyed	37	14.6917	0.3852	0.001
Destroyed	72			

Table 5 Vulnerability and susceptibility factors

Susceptibility		Chi-square	Q	P -value
<i>Early warning</i>				
Not warned	71	9.6744	0.3126	0.008
Warned	28			
<i>Training</i>				
Not trained	72	30.934	0.5590	<0.001
Trained	27			
<i>Relief</i>				
Not received	66	15.1985	0.3918	0.001
Received	33			
<i>Prediction means</i>				
None	13	14.8131	0.3868	0.005
radio/phones	34			
indigenous	52			

2.7.7 Vulnerability of households to flood disasters

The results reveal that the proportional odds of an exposed, susceptible and resilient relative to not exposed, not susceptible and not resilient, respectively. The results show that an exposed household has the odds of 20.68 times higher of being less vulnerable compared to that of being combined more and most vulnerable. For a susceptible household, the odds of being most vulnerable was 4.07 times higher than that of being more and less vulnerable. Similarly, a susceptible household in GVH Matani had the odds of 4.07 times higher of being less vulnerable compared to the combined odds of more and most vulnerable to flood

disasters. For a resilient household, the odds of being most vulnerable in the study area was 92.8% times less than the combined odds of being less and more vulnerable (Table 8).

2.7.8 Proportional odds assumption

Proportional odds assumption was carried out on the ordered logistic regression model of vulnerability as a response variable and exposure, susceptibility and resilience as explanatory variables. The hypothesis of this assumption was; H_0 : *There was no coefficient variation among levels of a response variable on a particular explanatory variable in the model.* A Likelihood-ratio test was carried out. The test revealed that Chi-square of 4.71 and P -value of 0.1942. According to the results above, p -value = 0.1942 which is greater than 0.05 significant level. Hence, we fail to reject a null hypothesis, and conclude that there was no coefficient variation among vulnerability levels (less vulnerable, more vulnerable and most vulnerable) on a particular explanatory variable (exposure, susceptibility and resilience) in the model. Therefore, the proportional odds assumption was not violated by the model and was applied in the analysis.

2.7.9 Prediction of vulnerability to flood disasters

The results show that when a household was not exposed, not susceptible and resilient to floods, the probabilities of being less vulnerable, more vulnerable and most vulnerable were 82%, 16% and 2%, respectively. For the households that were not exposed, not resilient but susceptible to floods, they had the probabilities of 8%, 46%, and 47% of being less, more and most vulnerable respectively. When the households were not exposed but susceptible and resilient, they had the probability of 53% of being less vulnerable, 41% of being more vulnerable and 6% of being most vulnerable. As regards the households that were exposed, susceptible and not resilient, the probabilities of

Table 6 Vulnerability and resilience factors

Resilience				
<i>House elevated</i>				
Not elevated	53	35.0557	0.5951	<0.001
Elevated	46			
<i>House repair</i>				
Not repaired	37	47.5538	0.6931	<0.001
Locally	11			
Standard	51			
<i>Protective wall</i>				
Not Protected	53	38.2549	0.6224	<0.001
Protected	46			
<i>Evacuation</i>				
Not evacuated	44	17.0519	0.4150	<0.001
Evacuated	55			
<i>River bank</i>				
Not raised	44	8.3302	0.2907	0.016
Raised	58			

Table 7 Factors affecting households vulnerability to floods

Vulnerability Less, more, most	Odds ratio	Z	P-value
Gender: Males*Females	32.0357	3.28	0.001
Evacuated	0.8078	−0.31	0.756
Elevation	1.2257	2.90	0.004
Prediction: None*radio, indigenous knowledge	0.9625	−0.04	0.971
	0.4412	−0.80	0.422
Forest depleted	1.9915	0.91	0.365
Trained	0.5814	−0.75	0.455
House type: Weak*strong very strong	0.05611	−3.40	0.001
	0.01747	−3.46	0.001
Protective wall	0.1671	−2.31	0.021

being less, more and most vulnerable were 0%, 5% and 95% respectively. The probabilities of being less, more and most vulnerable were 5%, 38% and 57%, respectively, for the households that were exposed, susceptible and resilient to flood disasters in GVH Matani.

Results in Table 9 are the post analysis results of multivariate analysis results in Table 8 above. Therefore, the thresholds in Table 8 and the Z values in Table 9 are used comparatively to assign a level of vulnerability to each combination of vulnerability components. In Table 8, $\alpha_0 = -1.103339$ and $\alpha_1 = 1.53484$ are the model thresholds. When Z in Table 8 is less than α_0 then that combination falls in the level of less vulnerable. If it is between the thresholds, then more vulnerable is satisfied. If Z is at least α_1 then, most vulnerable is satisfied. Therefore, Table 8 shows that when a household is either not exposed, not susceptible and resilience or not exposed, susceptible and resilient, it is found to be less vulnerable. The household that was not exposed, susceptible and not resilience was found to be more vulnerable in GVH Matani. For the households that were exposed, susceptible and not resilient or exposed susceptible and resilience were found most vulnerable.

Table 8 Modelling vulnerability with respect to exposure, susceptibility and resilience Log likelihood = −60.678247 Pseudo R2 = 0.4319

Vulnerability Less*more most	Odds ratio	Z	P-value
Exposure	20.68143	4.55	0.000
Susceptibility	4.067891	2.08	0.037
Resilience	0.0718439	−3.97	0.000
α_0	−1.103339		
α_1	1.53484		

Less* was a baseline category for vulnerability, LR χ^2 (3) = 92.25, P-value = 0.0000

2.7.10 Prediction margins of villages based on components of vulnerability

Figure 3 shows the probabilities of vulnerability based on exposure for the households in the villages of GVH Matani. The results show that the probabilities of less vulnerable for exposed households were 5% in Eliya, 8% in Chipamila, 18% in Redson, 7% in Fundi, 32% in Fasoni, 2% in Matani and 7% in Shalison. The households that were not exposed had the probabilities of 26% in Eliya, 33% in Chipamila, 53% in Redson, 32% in Fundi, 70% in Fasoni, 14% in Matani and 32% in Shalison of being less vulnerable.

Figure 4 shows the probabilities of vulnerability based on susceptibility for the households in the villages of GVH Matani. The results show that the probabilities of less vulnerable for a susceptible household were 14% in Eliya, 20% in Chipamila, 37% in Redson, 18% in Fundi, 51% in Fasoni, 5% in Matani and 18% in Shalison. The households that were not exposed had the probabilities of 44% in Eliya, 51% in Chipamila, 65% in Redson, 49% in Fundi, 76% in Fasoni, 29% in Matani and 49% in Shalison of being less vulnerable.

Figure 5 shows the probabilities of vulnerability based on resilience for the households in the villages of GVH Matani. The results show that the probabilities of less vulnerable for a resilient household were 25% in Eliya, 32% in Chipamila, 50% in Redson, 30% in Fundi, 66% in Fasoni, 14% in Matani and 30% in Shalison. The households that were not resilient had the probabilities of 5% in Eliya, 9% in Chipamila, 19% in Redson, 8% in Fundi, 31% in Fasoni, 2% in Matani and 8% in Shalison of being less vulnerable (Fig. 6).

2.7.11 Predictive margins of villages in GVH Matani

Graph 5 shows the probability of being less vulnerable based on the village interacting with exposure, susceptibility and exposure of the respondents. The results show that the probabilities of being less vulnerable were 0.227 for Eliya village, 0.286 for Chipamila, 0.427 for Redson, 0.268 for Fundi, 0.541 for Fasoni, 0.129 for Matani and 0.267 for Shalison. Similarly, the results provide the probabilities of being more and most vulnerable based on the village of the respondents. The probabilities of being more and most vulnerable were 0.777, 0.714, 0.573, 0.732, 0.459, 0.871 and 0.733 for Eliya, Chipamila, Redson, Fundi, Fasoni, Matani and Shalison villages, respectively.

All the predictive margins graphs in this section show the probabilities of households' vulnerabilities for a particular village based on vulnerability components. The village with more exposed, susceptible and not resilient households is more likely to be more and most vulnerable. Village Matani has the highest (87%) predictive margins of being more and most vulnerable to flood disasters. This is the case because majority of the households in the village are exposed (70%), susceptible (90%) and 60% are resilient to flood disasters.

Table 9 The predictions of vulnerability level under some conditions

Vulnerability factors			$Z = \beta_i x_i$	Probability ($Y = j$) in %		
Exposure	Susceptibility	Resilience		Less	More	Most
0	0	1	-2.6333	82	16	2
0	1	0	1.4031	8	46	47
0	1	1	-1.2301	53	41	6
1	1	0	4.4324	0	5	95
1	1	1	1.7991	5	38	57

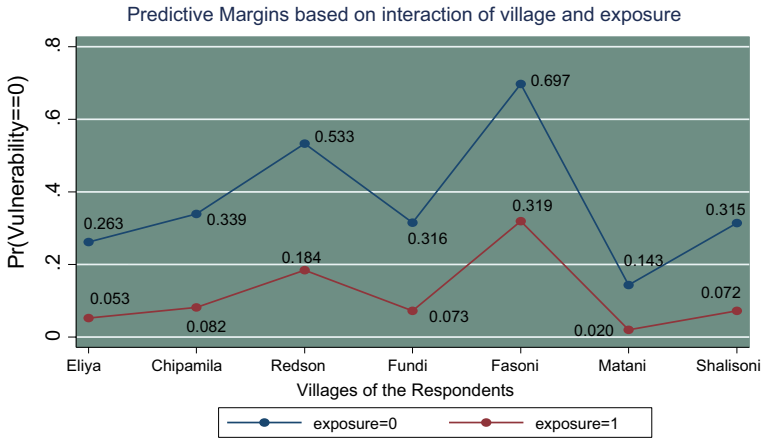


Fig. 3 Interactive predictive margins on villages under exposure

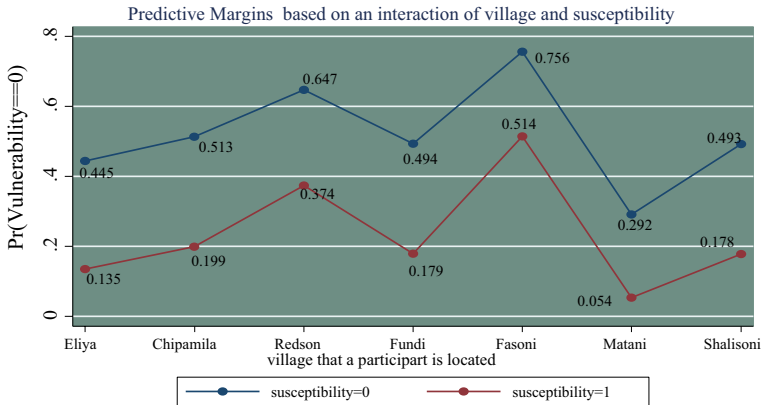


Fig. 4 Interactive prediction margins on villages under susceptibility conditions

Village Fasoni has the least (46%) predictive margins of being more and most vulnerable to flood disasters. In Fasoni village 100% of the sampled household were not exposed, (88%) susceptible households and 100% are resilient to flood disasters.

The likelihood of vulnerability level in each village is determine by the extent of exposure and susceptibility and the ability to cope with and recover from the impacts of flood disasters. There can be several combinations of the households in terms of exposure, susceptibility and resilience that provide a predictive margin of each village in GVH Matani. However, the whole idea is centred on that vulnerability level of the households to flood disasters is determined by balancing of exposure, susceptibility and resilience. Despite the descriptive variations that exist among the village predictive margins, the test (p value=0.1623) shows that they are not significantly different. This concludes that households in different villages have the same likelihood of vulnerability level to flood disasters in GVH Matani.

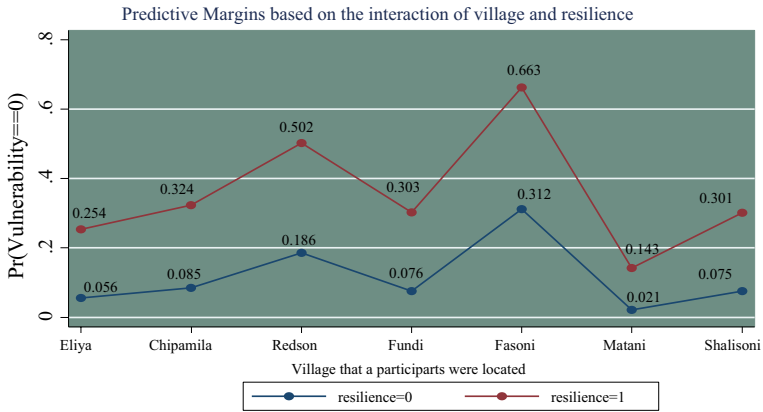


Fig. 5 Interactive prediction margins on villages under resilience conditions

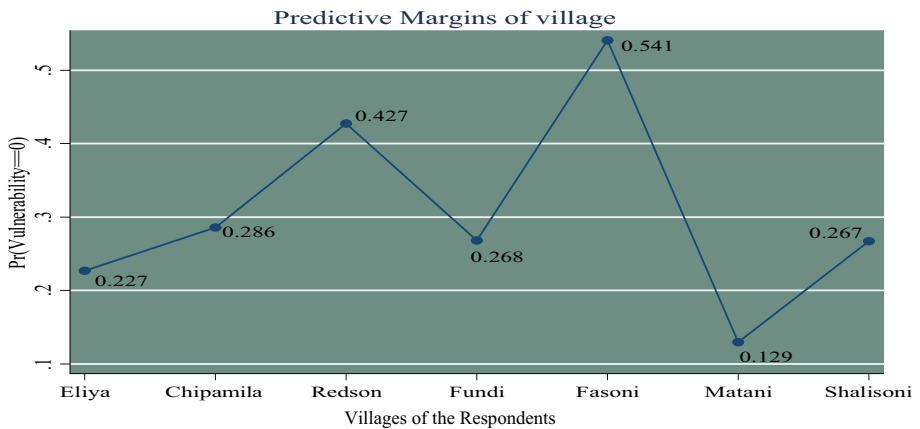


Fig. 6 Likelihood of vulnerability amongst the villages

2.8 Discussion

This study established that exposure of households is accelerated by the geographical terrain, closeness of households to the hazard sources, household size and altitude. These findings correlate with earlier studies such as a local scale flood vulnerability of Nazeer et al. (2020) in Pakistan. Majority of the households are located in the open flat fields, closer to the rivers and at lower altitude as a result they experience floods every year standing at high chances of being affected which increases household’s vulnerability to flood disasters. The household size was also large with the average size of 6 individuals per household. This maximizes the likelihood of increasing flood disasters risks. Household size also increases pressure on resources such as land. People do not have enough to accommodate them all, as a result they are cultivating along the riverbanks, a situation which creates a way for floods. Further, household size enables people to live in flood prone areas as they have no option and worth still their houses are not such strong due lack of financial capabilities. Household vulnerability in the area was accelerated by exposure.

This study further found that household's vulnerability to flood disasters was also high because majority of the households were susceptible to flood disasters. People were susceptible to flood disasters because majority of them were not being given early warning about the occurrence of floods in the area. This finding is consistent with the earlier studies which established lack of warnings contribute to vulnerability of people to floods (Munyani et al. 2019). In the area of the current study, majority of people use indigenous knowledge to predict the occurrence of floods that not always provides the relevant information about the occurrence of disasters. Therefore, households are most vulnerable because the community lack awareness and understanding of their capacity and position in the disaster management system. The households in the area do not know when and how to prepare for floods. This is because they are not involved in the planning, implementation and assessment of disasters risk reduction plans at community and local levels.

Vulnerability level to flood disasters increases when the exposed and susceptible households are not resilient to flood disasters. Households in this study were considered resilient when they were able to cope, to recover and to resist the impact of flood disaster during and after the flood disaster. Majority of the households in the area are not resilient to flood disasters. This was the case because most of them live in the poverty cycle. Majority of them are local farmers such that farming is a main source of income and food. However, agricultural farms and outputs are amongst the most affected by floods. Therefore, people find it challenging to find income that can help them to anticipate the impact of flood disasters, hence not resilient to flood disasters. The understanding of this study is that poverty is a measure of income level of a household. That is to say, a household with enough income level will be less poor thereby become more resilient and vice versa. Therefore, these findings point out to the notion that programming current and future flood disaster mitigation plans and vulnerability reduction measures, require formulation of relevant financial and economic measures which may contribute to poverty alleviation in community and society in order to promote resilience.

Households' vulnerability is also determined significantly by the gender, altitude and type of houses. Majority of the most vulnerable households were female headed. Women have 32.04 times higher odds of being more and most vulnerable relative to that of men headed households. This is in line with what Nabegu (2018) in Nigeria established that female were the most victims 72% of flood disasters. Despite that, some literature suggests women are more likely to recognize and respond to risk, women tend to be poorer relative to men and may not have the necessary resources to respond to and recover from disasters. Women vulnerability to disasters is also determined by traditional gender roles, power, privileges, and secondary responsibilities such as childcare. In addition, this might be reasons for women headed families in GVH Matani for being more and most vulnerable to flood disasters.

The type of houses also determines vulnerability level for the households in GVH Matani. Houses were categorized into three categories; weak, strong and very strong houses based on age of the house, material used as whether iron roofed or thatched, mud or burnt bricks, and concrete floor or not. Strong houses that are old aged, burnt bricked, iron roofed and no concrete floor have 0.056 less times odds of being more and most vulnerable to flood disasters in relation to weak houses. Very strong houses have 0.017 less times odds of being more and most vulnerable. This shows that weak houses constructed with mud and thatched have higher odds of being more and most vulnerable to flood disasters compared to strong and very strong houses. Weak houses tend not to withstand and adapt the pressure released by floods in the area. For similar reason the study also found that households that have houses that have protective wall, have less odds 0.67 times of being more

and most vulnerable. This shows that households that have houses with no protective wall have high chances of being more and most vulnerable to flood disasters.

Occupation of the household head was also found to be not a significant factor of vulnerability to flood disasters. Occupation was also categorized into either a respondent was a businessperson, farmer or fisherman. Majority of the respondent were crop farmers and 100% of the most vulnerable households were farmers. Majority of the less vulnerable households were those that were either doing business or fishing. Despite the fact that occupation was not significant, descriptive analysis results show that majority of fishermen and businesspersons were less vulnerable to flood disasters but crop farmers were more and most vulnerable to flood disasters. Farmers tend to be more and most vulnerable to flood disasters because most of their livelihood depends on the produce that get affected by floods. As a result, their income level decreases such that they cannot even cope with and recover from the impact of flood disaster. Fishermen and businessmen generate enough money during the period of floods and after because majority of households depend on the market for their food. Therefore, they can be able to recover the shock of flood disasters.

2.9 Conclusion and recommendations

This study found that no significant likelihood difference of being less vulnerable among the seven villages in GVH Matani. Despite the test, different villages have different predictive margins of vulnerability level. The difference in vulnerability level was due to some variation in exposure, susceptibility and resilience characteristics to flood disasters. Amongst the villages, village Matani has the highest probability of being more and most vulnerable whereby Fasoni village has the least chances of being more and most vulnerable to flood disasters. Therefore, more efforts should be done to reduce exposure and susceptibility and increase resilience in the villages in order to mitigate flood disaster risks in GVH Matani of T.A. Kilupula in Karonga district.

Therefore, this study recommends that vulnerability assessment should be included in disaster risk reduction (DRR) planning and implementation in order to make DRR more efficient and realistic. This would strengthen the disaster risk management to be more proactive as well as increase resilience of households to flood risks. The relationship between DRR and human rights needs to be explored and practical measures should be done in conjunction in order to strengthen it. To ensure the full and effective participation of local people, it is particularly crucial to seek and include the perspective of local women, children and person with disabilities.

2.10 Ethical issues

Ethical approval was sought from the Mzuzu University Research Ethics Committee (MZUNIREC) with reference No. MZUNIREC/DOR/21/37. The MZUNIREC Permission was submitted to Karonga District Council (KDC). Participants were assured of confidentiality.

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Declarations

Conflict of interest The Authors declare that they have no known competing financial interest or personal relationships that could have appeared to influence the work reported in this research paper.

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