EFFECT OF DEMOGRAPHIC AND SOCIO-ECONOMIC FACTORS ON COMMUNITY RESILIENCE TO FLOOD HAZARD IN CALABAR SOUTH LOCAL GOVERNMENT AREA OF CROSS RIVER STATE, NIGERIA

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ABSTRACT

Flooding remains a significant environmental challenge globally, disproportionately affecting vulnerable populations in urban and low-lying areas. In Calabar South Local Government Area (LGA) of Cross River State, Nigeria, recurring flood events pose severe risks to lives, livelihoods, and infrastructure. This study investigated the influence of socio-economic and demographic factors on community resilience to flood hazards in three flood-prone communities: Jebs/Ibesikpo, Anantigha, and Eneobong Avenue. Using a cross-sectional survey design, 585 copies of structured questionnaire were administered to household heads, and data were analyzed through multiple regression modeling. The dependent variable (community resilience) was operationalized as perceived recovery speed from flood events. Independent variables included income level, educational attainment, age, gender, and household size. Findings revealed that 73.6 per cent of households rated their flood recovery as either "slow" or "very slow." Regression results demonstrated a statistically significant model ($R^2 = 0.529$, $p < 0.001$), indicating that over half the variation in resilience could be explained by the selected socio-economic and demographic variables. Income ($B = 0.244$) and education level ($B = 0.125$) had significant positive influences on resilience, highlighting the importance of financial resources and awareness in disaster preparedness and response. Conversely, household size ($B = -0.281$), age ($B = -0.151$), and gender ($B = -0.125$) were negatively associated with resilience, suggesting that larger households, older individuals, and women perceive themselves as less able to recover from flood impacts. These findings align with existing literature that emphasizes the role of socio-economic vulnerability in shaping disaster outcomes. The study concluded that socio-demographic characteristics are critical determinants of flood resilience. Therefore, local, state and federal governments should incorporate these variables into disaster risk reduction (DRR) strategies. Tailored interventions, such as gender-sensitive policies, income support programs, education campaigns, and inclusive community planning, are essential to enhancing resilience among at-risk populations. The results serve as a vital reference for policy formulation aimed at reducing flood vulnerability and promoting sustainable urban resilience in Calabar South and similar flood-prone regions.

KEYWORDS: *Flood Resilience, Socio-Economic Factors, Community Vulnerability, Disaster Risk Reduction, Calabar South, Nigeria.*

1. INTRODUCTION

Flood hazards remain one of the most frequent and devastating natural disasters globally, with significant impacts on lives, livelihoods, infrastructure, and health, especially in vulnerable communities. In Calabar South Local Government Area (LGA) of Cross River State, Nigeria, recurring flood events have raised concerns over the capacity of communities to withstand and recover from such disasters. Existing studies suggest that demographic and socio-economic factors significantly influence the level of resilience within flood-prone communities.

Demographic characteristics such as gender and age are critical determinants of community resilience to floods (Ahmad & Afzal, 2020; Koks, Jongman, Husby, & Botzen, 2015; Scherzer, Lujala, & Rød, 2019; Soetanto, Mullins, & Achour, 2017). They help explain why two individuals in the same location may respond differently to flood-related risks (Soetanto et al., 2017). For instance, identifying vulnerable groups based on gender and age improves human security and resilience strategies such as constructing appropriate shelters and developing gender-sensitive policies (Koks et al., 2015). A survey after the 2014 floods in Serbia confirmed that gender influences flood perception, preparedness, and response (Cvetković, Roder, Öcal, Tarolli, & Dragićević, 2018). Similar findings in Ireland revealed gender-based differences in risk perception, with women being more internally focused (e.g., boiling water) and men exhibiting external risk-mitigation behaviours (e.g., placing sandbags) (McDowell, Ní Bhroin, Delaney, & Hyland, 2020). However, traditional gender roles still dominate in many contexts, limiting adaptive behaviour despite heightened awareness (O'Neill, Brereton, Shahumyan, & Clinch, 2016).

Socio-economic status, including income, employment, and homeownership, affects flood response and recovery (Khoja, Othman, Abidin, & Al-Amin, 2020; Rufat, Tate, Burton & Maroof, 2015). Those with lower income are often less adaptable, while the wealthy, despite greater potential asset losses, demonstrate stronger resilience (Rufat et al., 2015). Key indicators of resilience include income, employment, car/home ownership, and access to health insurance (Khoja et al., 2020). Langkulsen, Rwodzi, Cheewinsiriwat, Nakhapakorn and Moses (2022) similarly conducted a socio-economic impact assessment of flood-affected populations in Thailand, reinforcing the importance of socio-economic resilience planning.

Household composition, including family size and the presence of dependents, also plays a role. In rural China, flood risk perception declined with larger household sizes but increased when children under 12 were present (Liu, Li, Shen, Xie & Zhang 2018). Similarly, households with children often demonstrate higher preparedness, while single-parent or elderly-only households are more vulnerable (Shah, Ye, Abid, Khan & Ullah, 2018).

Social capital, particularly collective forms, enhances resilience by fostering cooperation and preparedness. A study in Ghana's Old Fadama showed that collective social capital was a stronger predictor of resilience than personal ties, emphasizing the need for community-based approaches (Abunyewah, Erdiaw-Kwasie, Okyere, Thayaparan, Byrne, Lassa, Zander, Fatemi, & Maund, 2023). Hallegatte, Bangalore and Vogt-Schilb (2016) showed that floods disproportionately affect the poor, and asset losses alone don't reflect true welfare impacts. They recommend policies like adaptive social protection that target welfare, not just asset loss.

It has been garnered from the above that socio-economic status such as income, employment, education, serves as a key determinant of flood resilience. Poor households often lack the financial means to implement preventive measures, recover from damage, or access quality healthcare during and after flood events. Given the increasing frequency and severity of floods in Cross River State, understanding how demographic and socio-economic factors influence community resilience is essential. Meanwhile several studies on flooding and its impact have been carried out in Calabar generally and Calabar South in particular (Efiong, Efiong, Akintoye, Inah, Awan & Ogban, 2024; Efiong & Bassey, 2025 in press; Efiong & Ushie 2019; Efiong & Hogan 2017; Ekpoh 2014; Eze, 2008). However, none of them considered socio-economic factors in flood resilience. This study therefore explored these dynamics in Calabar South LGA to inform targeted policy interventions, community planning, and disaster risk reduction strategies tailored to local vulnerabilities and capacities

2 MATERIALS AND METHODS

2.1 Study area description

This study was conducted in three (3) flood prone communities in Calabar South Local Government Area of Cross River State in Nigeria. Calabar South Local Government Area lies between Longitudes $8^{o}15'$ and $8^{o}25'$ East of the Greenwich Meridian and Latitudes $4^{0}40'$ and $5^{0}05'$ North of the Equator (FIG. 1). Calabar South is generally a low land on an average of 64 metres above sea level. It is a cosmopolitan urban area. It is bounded to the North by Calabar Municipality, to the South and East by the Great Qua River and to the West by the Calabar River. It has a landmass of $264km^{2}$ (approximately). Much runoff during rainy season is emptied into Calabar South from the neighbouring Calabar Municipality and its areas with relatively higher elevations.
Calabar South has a population of 191,630 people, according to National Population Census (NPC) of 2006. The climate is tropical monsoon climate with an average annual temperature of $25.8^{0}C$ and annual average rainfall of 3306mm. Calabar South has a lengthy wet season spanning 8-9 months (March to November) and a short dry season covering the remaining part of the year. Temperature is relatively constant throughout the year, with average high temperature usually ranging from 25 to 28 degrees Celsius. Harmattan, which significantly influences weather in West Africa, is noticeably less pronounced in the area.

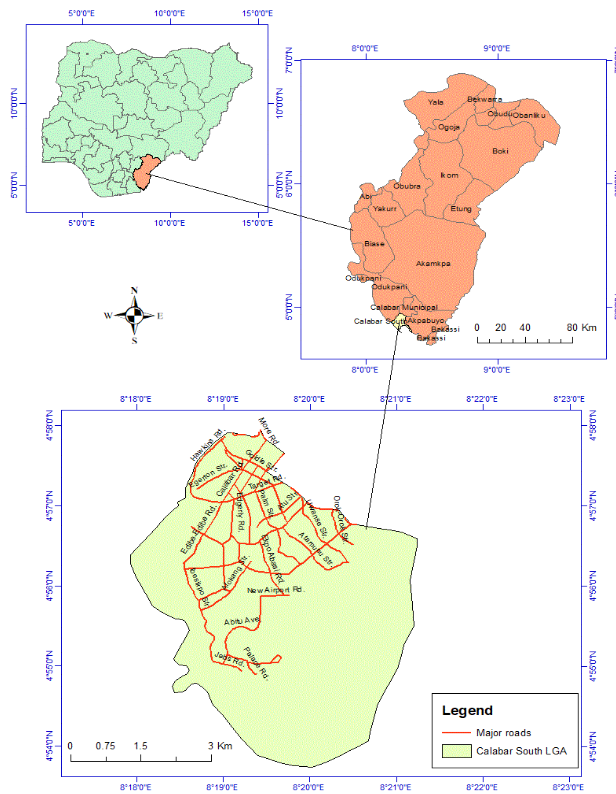

FIG. 1. Study area location
Source: GIS Laboratory, Department of Geography and Environmental Science, University of Calabar (2023).

2.2 Study design

This study employed a quantitative, cross-sectional survey design, using a structured questionnaire administered across three coastal communities: Jebs/Ibesikpo, Anantigha, and Eneobong Avenue. Respondents were selected using a stratified random sampling method to ensure proportional representation from each community. The questionnaire was administered to the household heads of the 585 selected sample houses. This distribution of the sample across the three locations are shown in Table 1, based on the targeted study population.

Table 1 Distribution of samples in the study

Location	Total Number of buildings	Minimum Sample
Jebs/Ibesikpo (A)	386	186
Anantigha (B)	511	242
Eneobong Avenue (C)	326	155
Total	**1233**	**585**

Source: Author's compilation (2024).

2.3 Variables Specification

Dependent Variable (Y)

Capacity to recover from flooding – This was operationalized using a Likert-scale-based categorical variable (very slowly, slowly, moderately fast, fast, very fast), which was recoded into a numerical index for regression analysis.

Independent Variables (X):

X_1 = Age: measured in ordinal scale

X_2 = Gender: measured in nominal scale (male and female)

X_3 = Educational Level: Coded numerically from 0 (no schooling) to 4 (postgraduate education).

X_4 = Income Level: Ordinally measured and transformed into numeric midpoints for regression (e.g., ₦30,000–₦100,000 = ₦65,000).

X_5 = Household size, measured ordinally.

2.4 Hypothesis

H_o: Demographic (age, gender, household size) and Socio-economic (income, educational level) factors do not significantly influence the capacity of coastal communities to recover from flooding in Calabar South LGA.

H_1: Demographic (age, gender, household size) and Socio-economic (income, educational level) factors significantly influence the capacity of coastal communities to recover from flooding in Calabar South LGA..

2.5 Model Specification

Multiple regression model was adopted to analyse the data for testing the hypothesis. The choice of this statistical test is because the researcher is interested in analysing the influence of several independent variables on a single dependent variable. The model is given as:

$$y = a + b_1x_1 + b_2x_2 + b_3x_3 + b_4x_4 + b_5x_5 + e$$

where;

y = Capacity to recover

X_1 = Age

X_2 = Gender

X_3 = Educational Level

X_4 = Income Level

X_5 = Household size.

$b_1 - b_5$ = regression coefficients

a = regression constant

e = Tolerable error term

3. RESULTS

Date obtained in this study are presented mostly in Tables. Table 2 presents data on age distribution of respondents across the three study locations (Jebs/Ibesikpo, Anangtigha and Eneobong Avenue). Cumulatively, majority of respondents (44.1 per cent) were in the age bracket of 35 – 44 years. This was followed by those in the range of 25 – 34 years (28.0 per cent) and then 12.5 per cent for those within the age bracket of 55 - 64 years. Respondents 65 years and above constituted the least in the sample with just 1.0 per cent those in the 18 – 24 years were only 9.7 per cent of the sample. There were no respondents below 18 years in the sample.

The distribution of gender in the sample is found in Table 3. Here, 65.1 per cent of the sample were males while the remaining 34.9 per cent were female. Hence, there were more males than females in the study sample. Meanwhile, educational level completed by respondents are distributed in Table 4 Here, only 0.5 per cent of respondents reported "No schooling completed. This was only recorded in Eneobong Avenue area. Secondary education with 41.09 has the highest number of respondents. This was followed by those who had completed undergraduate education (31.1 per cent) and then those with primary education (24.1 per cent). Respondents with postgraduate education made up the remaining 3.2 per cent.

TABLE 2: Age distribution of respondents

Age Group (Years)		Location: Jebs/ Ibesikpo Area	Anantigha Area	Eneobong Avenue Area	Total
< 18	Count	0	0	0	0
	% of Total	0	0	0	0
18-24	Count	11	28	18	57
	% of Total	1.9	4.8	3.1	9.7
25-34	Count	58	70	41	169
	% of Total	9.9	12.0	7.0	28.9
35-44	Count	85	101	72	258
	%of Total	14.5	17.3	12.3	44.1
45-54	Count	21	34	18	73
	%of Total	3.6	5.8	3.1	12.5
55-64	Count	10	9	3	22
	% of Total	1.7	1.5	0.5	3.8
65 and above	Count	1	3	2	6
	% of Total	0.2	0.5	0.3	1.0
Total	Count	186	245	154	585
	% of Total	31.8	41.9	26.3	100.0

Source: Authors' fieldwork (2024)

TABLE 3: Gender distribution

Gender		Location Jebs/ Ibesikpo Area	Anantigha Area	Eneobong Avenue Area	Total
Male	Count	122	150	109	381
	% of Total	20.9	25.6	18.6	65.1
Female	Count	64	95	45	204
	% of Total	10.9	16.2	7.7	34.9
Total	Count	186	245	154	585
	% of Total	31.8	41.9	26.3	100.0

Source: Authors' fieldwork (2024)

TABLE 4: Educational level

Education Level			Location Jebs/ Ibesikpo Area	Anantigha Area	Eneobong Avenue Area	Total
	No schooling completed	Count	0	0	3	3
		% of Total	0.0	0.0	0.5	0.5
	Primary Education	Count	44	72	25	141
		% of Total	7.5	12.3	4.3	24.1
	Secondary education	Count	73	97	70	240
		% of Total	12.5	16.6	12.0	41.0
	Undergraduate education	Count	65	66	51	182
		% of Total	11.1	11.3	8.7	31.1
	Postgraduate education	Count	4	10	5	19
		% of Total	0.7	1.7	0.9	3.2
Total		Count	186	245	154	585
		% of Total	31.8	41.9	26.3	100.0

Source: Authors' fieldwork (2024)

Table 5 presents data on household income per month (₦) from the table, 34.7 per cent earned monthly income of less than ₦30,000; 39.0 per cent earned between ₦30,000 and ₦100,000 per month while 13.0 per cent earned between ₦101,000.00 and ₦50,000 per month. Also, 9.2 per cent earned between ₦251, 000 and ₦500, 000 while 4.1

per cent earned above ₦500, 000 per month. The table reveals that most of the respondents earned above ₦30,000.

TABLE 5: Household income per month (₦)

Household income per month (₦)		Location: Jebs/ Ibesikpo Area	Anantigha Area	Eneobong Avenue Area	Total
< ₦ 30,000	Count	32	40	24	96
	% of Total	5.5	6.8	4.1	16.4
₦ 30,000-100,000	Count	91	108	70	269
	% of Total	15.6	18.5	12.0	46.0
₦ 101,000-250,000	Count	42	62	39	143
	% of Total	7.2	10.6	6.7	24.4
₦ 251,000-₦ 500,000	Count	15	25	15	55
	% of Total	2.6	4.3	2.6	9.4
> ₦ 500, 000	Count	6	10	6	22
	% of Total	1.0	1.7	1.0	3.8
Total	Count	186	245	154	585
	% of Total	31.8	41.9	26.3	100.0

Source: Authors' fieldwork (2024)

Table 6 presents data on the rate of recovery from flood hazard in the study area, from table 30, 30.9 per cent of the sample recovered from flood hazard very slowly, 42.7 per cent selected "slowly" as their option while 13.2 per cent went for "moderately fast". About 8.9 per cent of

TABLE 6: Rate of community recovery from a flood event

Rate of community recovery from a flood event		Location: Jebs/ Ibesikpo Area	Anantigha Area	Eneobong Avenue Area	Total
Very slowly	Count	66	75	40	181
	% of Total	11.3	12.8	6.8	30.9
Slowly	Count	82	105	63	250
	% of Total	14.0	17.9	10.8	42.7
Moderately fast	Count	20	31	26	77
	% of Total	3.4	5.3	4.4	13.2
Fast	Count	13	21	18	52
	% of Total	2.2	3.6	3.1	8.9
Very fast	Count	5	13	7	25
	% of Total	0.9	2.2	1.2	4.3
Total	Count	186	245	154	585
	% of Total	31.8	41.9	26.3	100.0

Source: Authors' fieldwork (2024).

respondents recovered fast, while the remaining 43 per cent chose very fast. Generally, the data reveals that most of the sample recovered slowly from flood hazard.

The multiple linear regression analysis investigates the extent to which socio-demographic variables (household size, gender, education level, age group, and household income) influence the perceived resilience of communities to flooding. The results of the multiple regression analysis are presented in Tables 7a, b and c. The results (Table 7a) indicate a strong and statistically significant model, with an R value of 0.727 and an R Square of 0.529, meaning that approximately 52.9 per cent of the variability in community resilience can be explained by the combined effect of these five predictors. The adjusted R Square of 0.525 confirms the model's robustness, accounting for the number of predictors included. The standard error of the estimate (0.625) shows the average deviation of observed responses from predicted responses.

The ANOVA table (Table 7b) further validates the model's significance. The F-statistic of 129.970 with a p-value of 0.000 suggests that the regression model significantly predicts the dependent variable—community resilience to flooding. This means that the set of independent variables collectively provides a statistically meaningful explanation of the variations in perceived flood resilience among the sampled households.

The coefficients table (Table 7c) provides insight into the individual contribution of each variable. Household size has the strongest negative influence on resilience ($B = -0.281$, $p < 0.001$), implying that larger households tend to perceive themselves as less resilient—possibly due to increased economic and logistical demands during flood events. Household income is a significant positive predictor ($B = 0.244$, $p < 0.001$), indicating that wealthier households feel more capable of coping with floods, likely due to better access to resources and infrastructure. Education level also has a positive effect ($B = 0.125$, $p = 0.001$), reflecting the role of awareness, knowledge, and preparedness in enhancing resilience (Figure 2).

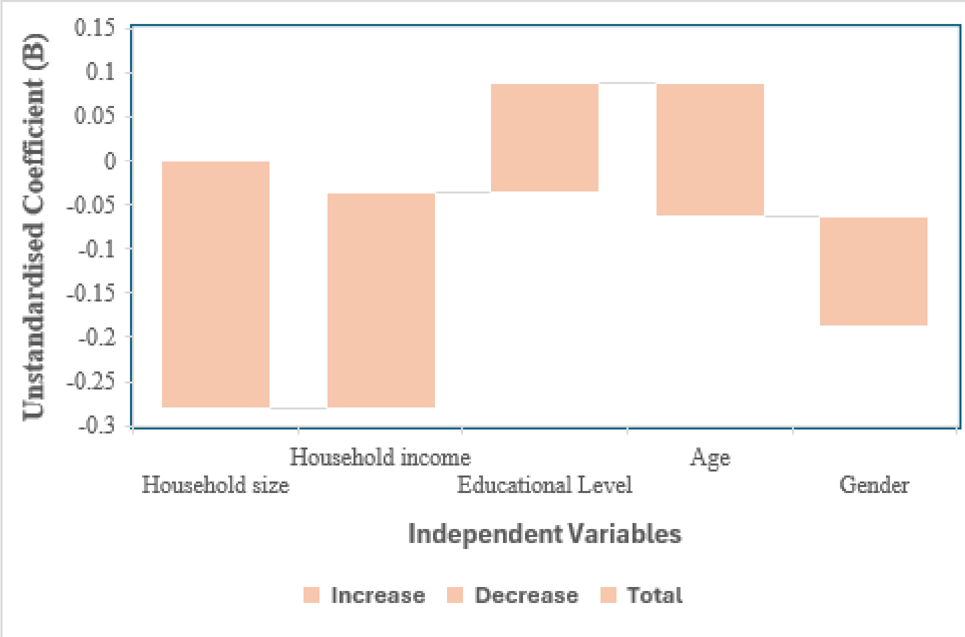

Figure 2. Contributions of independent variables to community cesilience

Age group is negatively associated with resilience (B = -0.151, $p < 0.001$), suggesting that older individuals or households with older members may feel more vulnerable to flood risks. Gender has a weaker but still statistically significant negative effect (B = -0.125, p = 0.037), possibly reflecting gender-based differences in risk perception, coping strategies, or social roles (Figure 2).

TABLE 7a: Regression model summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.727[a]	.529	.525	.62545

Source: Authors' statistical analysis (2024).

TABLE 7b: Analysis of variance

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	254.213	5	50.843	129.970	.000[b]
	Residual	226.498	579	.391		
	Total	480.711	584			

Source: Authors' statistical analysis (2024).

TABLE 7c: Regression coefficients

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	T	Sig.
1	(Constant)	2.644	.167		15.876	.000
	Age Group	-.151	.020	-.246	-7.735	.000
	Gender	-.125	.060	-.069	-2.095	.037
	Education Level	.125	.037	.115	3.391	.001
	Household income per month (₦)	.244	.032	.267	7.543	.000
	Households size	-.281	.023	-.397	-12.463	.000

Source: Authors' statistical analysis (2024).

To determine which independent variable, contribute most to the variation in the dependent variable (community resilience) based on the t-values, we evaluated their absolute t-values — the larger the absolute t-value, the greater the contribution (i.e., the stronger the evidence against the null hypothesis that the coefficient is zero) (Table 8).

TABLE 8: Ranking of independent variables by contribution (based on |t-value|)

Rank	**Variable**	**t-value**	**Absolute t-value**	**Contribution**
1	Household Size	-12.463	**12.463**	Highest
2	Age Group	-7.735	**7.735**	High
3	Household Income	7.543	**7.543**	High
4	Education Level	3.391	**3.391**	Moderate
5	Gender	-2.095	**2.095**	Lowest

Source: Authors' compilation from Table 6c (2024)

From Table 8, household size is the strongest predictor of perceived resilience. Age group and income both have strong impacts, but in opposite directions (age: negative; income: positive).

Education level makes a moderate contribution and enhances resilience. Gender has the weakest statistically significant effect, though it still matters. This ranking helps identify priority areas for intervention, e.g., policies targeting larger households and older residents may yield the most improvement in flood resilience.

Using the unstandardized coefficient, the regression model is therefore presented as follows:

$$\text{Community Resilience} = 2.644 - 0.151(\text{Age Group}) - 0.125(\text{Gender}) + 0.125(\text{Education Level}) + 0.244(\text{Household Income}) - 0.281(\text{Household Size})$$

Interpretation of the Regression Model

Intercept (2.644): This is the predicted community resilience score when all independent variables are equal to zero. Although this value may not have a practical interpretation (as values like age or income cannot realistically be zero), it serves as a baseline for the regression equation.

Age Group (-0.151): For each one-unit increase in the age group category, the perceived community resilience to flooding decreases by 0.151 units, assuming all other variables remain constant. This suggests that older individuals perceive their communities as less resilient.

Gender (-0.125): Holding other factors constant, a one-unit change in gender, from male to female leads to a decrease of 0.125 in the resilience score. This implies a gender-based difference in perception, with female gender perceiving less resilience than the other.

Education Level (+0.125): A one-unit increase in education level (e.g., moving from primary to secondary education) increases the resilience score by 0.125 units, assuming other factors are constant. Higher education is associated with greater perceived community resilience.

Household Income (+0.244): For each one-unit increase in income (based on the scale used), the resilience score increases by 0.244 units. This shows that households with higher income tend to perceive their communities as more resilient to flooding.

Household Size (-0.281): A one-unit increase in household size results in a 0.281 unit decrease in the perceived resilience score. Larger households are more likely to perceive their community as less resilient to flooding, possibly due to increased dependency and resource constraints

4. DISCUSSION

The aim of this study was to examine the effect of socio-economic variables such as educational level and income on community resilience to flood hazard in Calabar south Local Government area of Cross River State, Nigeria. The findings from the regression analysis provide valuable insights into the socio-demographic factors influencing perceived community resilience to flooding. The results show that household size, gender, age, education level, and household income significantly affect how communities rate their resilience to flood events. These findings align with several previous studies that have explored similar variables in the context of disaster risk perception and community resilience.

First, the negative effect of household size on perceived resilience suggests that larger households are more likely to feel vulnerable during flood events. This may be due to the increased financial and logistical burden associated with protecting more individuals, especially children or dependents, during emergencies. According to Cutter, Barnes, Berry, Burton, Evans, Tate and Webb (2008), larger households often require more resources and coordinated planning, which may lower their adaptive capacity during disasters. Similarly, Fatemi, Ardalan, Aguirre, Mansouri and Mohammadfam (2017) noted that household size is a significant determinant of vulnerability in flood-prone regions, especially in developing countries.

The positive relationship between education level and resilience reflects the critical role of awareness, knowledge, and preparedness in disaster response. Educated individuals are generally more likely to access early warning systems, understand flood risks, and adopt appropriate mitigation strategies. Paton (2003) emphasizes that higher education levels are associated with proactive coping strategies and improved individual and collective decision-making during disasters. Aksha, Juran, Resler & Zhang (2020) also affirms that education contributes to risk awareness and enhances community resilience by promoting informed actions. Educated individuals are generally more informed on flood risk mitigation and can better understand early warning systems, emergency procedures, and recovery resources, as supported by recent studies such as those by Wang & Zhang (2023). Education has been widely recognized as a key factor in building resilience, as it equips community members with the skills to seek, comprehend, and act on information essential for reducing vulnerability and ensuring faster recovery.

Similarly, household income significantly enhances perceived resilience. Higher-income households have better access to protective infrastructure, insurance, emergency savings, and the ability to relocate if necessary. This aligns with the findings of Brouwer, Akter, Brander and Haque (2007) and Cutter, Burton and Emrich (2010), who found that income is one of the strongest predictors of disaster resilience due to its link to financial security, access to information, and adaptive resources. Also, this finding aligns with recent research by Abunyewah et al. (2023), who found that higher household income significantly improves flood resilience by providing means for immediate response and sustained recovery efforts. Financial resources directly impact a household’s ability to replace lost assets, repair damaged infrastructure, and invest in flood-resistant adaptations, all of which are critical for long-term resilience.

Conversely, the negative coefficient for age group indicates that older individuals tend to perceive their communities as less resilient. This perception may stem from declining physical strength, increased dependence on others, or reduced mobility, which limit older adults' ability to respond effectively during floods. HelpAge International (2014) observed that aging populations are more vulnerable during natural disasters and often face systemic exclusion from emergency planning processes. Fernandez, Byard, Lin, Benson and Barbera (2002) also emphasized that older adults are less likely to evacuate quickly and often lack access to recovery resources.

Lastly, the negative impact of gender on perceived resilience—albeit weaker—suggests possible gender disparities in flood risk perception and response capacities. This might be due to women's disproportionate roles as caregivers or limited access to decision-making platforms in some communities. Studies such as those by Enarson and Chakrabarti (2009) and Neumayer and Plümper (2007) highlight how gender shapes disaster experiences, with women often bearing greater physical and psychological burdens during and after floods, particularly in patriarchal societies.

5. CONCLUSION

In conclusion, the regression model confirms that socio-demographic factors are significant predictors of perceived flood resilience. These findings underscore the need for inclusive and context-specific disaster risk reduction (DRR) policies that account for household composition, gender dynamics, income disparities, education levels, and age-related vulnerabilities. Targeted interventions could empower disadvantaged groups through education, economic support, and participatory planning will be essential in enhancing resilience and reducing flood-related risks. In view of the above, governments at all levels (Local, State and Federal) should implement support programmes focused on improving economic resilience, such as providing micro-finance options for low-income households and vocational training to diversify income sources.

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