Influence of Socioeconomic Factors on Coastal Households' Vulnerability to Flood in South-South, Nigeria

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Abstract

The study evaluated the influence of socioeconomic factors on coastal households' vulnerability to flood in South-South Nigeria. Systematic sampling technique was used to administer 632 copies of structured questionnaire to coastal households in Rivers, Delta and Bayelsa States. Data obtained from the administered questionnaire were analyzed using simple percentages and logistic regression analysis. Results found occupation and sex to significantly predict household exposure to flood with occupation (OR = 4.74) having higher predictability. Also, occupation (X^2=33.566, $p<0.05$) and monthly income (X^2=10.648, $p<0.05$) significantly predicted household adaptive capacity to flood with monthly income (OR = 1.000) having higher predictability. As a result of the low financial base of the households, the study encouraged government and private individuals to improve the adaptive capacity of flood prone communities by putting in place structural adaptive measures of flood control.

Keywords: socioeconomic, vulnerability, coastal households, adaptive capacity, preparedness

1. Introduction

Coastal communities all over the world are vulnerable to flood and one of the major contributory factor is their socioeconomic characteristic. The socioeconomic characteristics of coastal communities play a tremendous role in determining households' ability to manage and reduce the devastating impact of flood. The social and economic status of coastal communities to a large extent determine their level of preparedness for flooding as well as influence households' decision of building location and building materials amongst other things. Wealthy households are able to build their houses in areas not liable to flooding which keep them safe from the rampaging effects of floods. This is not the case with poor households who occupy flood prone areas even when they know the inherent consequences. Poor households have low adaptive capacity to flood due to their low income which prevents them from putting in place flood preventive measures.

As such, they are usually victims of any flood episode or event. In addition, social cohesion and effective leadership among households in coastal areas can have a substantial impact on their fight and preparedness for flood. When households have good cooperation and understanding, they are able to come together and devise a better way or measure in flood management. One way of achieving this is through financial contribution which enables long-lasting an effective structural measures of flood management to be put in place. This approach helps to reduce the risks associated with flooding. Studies Rufat, Tate, Christopher, Burton & Maroof (2015) and Adeleke (2013) among several others have shown the roles the socioeconomic characteristics of households in coastal communities play in flood management. The study by Rufat et al., (2015) identified demographic and socioeconomic characteristics as well as health status as the leading drivers of social vulnerability to damaging flood events in Africa.

In another study, Liu and Li (2016) suggested improving in household income among others as measures to reduce household social vulnerability to flood hazards. The study by Nkwunonwu (2017) in Lagos State, Nigeria found high indices of social vulnerability to pluvial flooding in Alimoso, Agege and Kosofe and also identified patterns of vulnerability based on demographic composition of the population; gender variation, socio-economic status, and family structure. These socioeconomic factors were found to have significant impacts on social vulnerability to pluvial flooding. Chisola (2012) found that households' vulnerability reduction strategies require an appropriate sustainable livelihood; and requires a person to be educated, employed and earned a sufficient monthly income. The study stated that household resilience and sustainable livelihood can be built when people are empowered and that social, physical, natural and financial capital reduces vulnerability and also promotes resilience. These studies among others have shown the contributory impacts of households' socioeconomic factors on flood management and vulnerability reduction. It is on this foregoing that the present study is carried out to further elucidate on the influence of socioeconomic factors on households' vulnerability flood, while suggesting ways to improve on the socioeconomic characteristics of households in the area of study in order to improve their adaptive capacity to flood.

2. Materials and Methods

Study area

The study area comprises households in Rivers, Delta and Bayelsa States. These states are located in the South – South region of Nigeria (Figure 1). It comprises six states of Akwa Ibom, Bayelsa, Cross River, Delta, Edo and Rivers State having a total area of 84,643 km^2. The South – South region of Nigeria is the second largest delta in the world with a coastline which spans about 450 kilometres and of course the richest wetland in the world (Awosika, 1995). The region is divided into four ecological zones namely coastal inland zone, mangrove swamp zone, freshwater zone and lowland rain forest zone (Awosika, 1995). The region is influenced by the localized convection of the West African monsoon with less contribution from the mesoscale and synoptic system of the Sahel. The monsoon rainy (wet) season over the area begins in May, as result of the seasonal northward movement of the Inter-Tropical Convergence Zone (ITCZ), with cessation in October. Fishing and agriculture are the two major traditional occupations of the Niger Delta peoples.

Types and sources of data

Primary data were basically used. Primary data were collected through the administration of questionnaire copies to households in coastal areas across the selected states. The data collected include: data on demographic and socioeconomic characteristics; data on levels of social vulnerability in terms of exposure, susceptibility and adaptive capacity of the households to flood. These data were categorical variables that show of how households across the selected States are exposed to flood, susceptible to flood and whether or not they have the adaptive capacity to cope with flood.

Sampling techniques

The study employed the multistage sampling technique involving three steps. The steps involved the interplay of purposive, simple random and systematic sampling technique. In the first step, purposive sampling technique was employed to select basically States in the south-southern region seriously affected by the 2012 and 2018 floods and the affected States were Rivers, Bayelsa, Delta and Edo States. The justification for the selection of these states (Rivers, Bayelsa, Delta and Edo) is that they were declared national disaster states on the account of flood by the NEMA in 2012 and 2018. More so, the States experience annual constant flooding. In the second step, simple random sampling technique was then used to select three states out of the four; the three randomly selected states were Rivers, Delta and Bayelsa States. In the third step, systematic sampling technique was employed during questionnaire administration. This technique enabled copies of structure questionnaire to be successfully administered to households in the selected States. This technique was chosen and employed due to the poor arrangement and numbering of houses in the coastal areas. As such, in each chosen street, the second building was chosen for questionnaire administration after which the fourth was picked in that manner. The interval between each surveyed household was three. Also, only one household head (male or female) was selected for the survey.

Sample size

In order to sample or survey a representative of the population across the selected states, the sample size was determined using Yamane's formula (1967). The Yamane, Taro's formula is as follows:

$$n = \frac{N}{1+N(e)^2} \quad \text{...} \quad \text{eqn(1)}$$

Where: n = sample size; N = Definite population of coastal communities in the selected states; e = level of precision or confidence level $(0.05)^2$

$$n = \frac{1,768,487}{1+1,768,487 \times (0.05)^2}$$

$$= \frac{1,768,487}{1+1,768,487 \times 0.0025}$$

$$\frac{1,768,487}{1+4421.22}$$

$$= \frac{1,768,487}{4422.22}$$

$$= 399.9$$

$$n \approx 400$$

Since the sample size is 400 for the vulnerable, frontline and coastal LGAs across the three States (Bayelsa, Rivers and Delta). But from field observation and experiences, not all questionnaire administered in the field would be retrieved back from the respondents and more so, some questionnaire may not be responded to. Therefore, the sample size was increased by multiplying the obtained figure by 2. The essence was to accommodate for these lapses. Hence, n = 2 × 400 = 800. The number of questionnaire copies administered to communities under States is shown in Table 1.

Table 1: Sample size for LGAs, their projected and household population

State	Name of LGA	Projected Population to 2018	Household Population per LGA	Number of Questionnaire per LGA
Bayelsa	Ekeremor	379,914	63,319	29
	Brass	259,479	4,246	20
	Kolokum/Opukuma	111,705	18,617	8
	Nembe	184,562	30,760	14
	Ogbia	25,108	42,185	19
	Sagbama	263,343	43,890	20
Rivers	Abua/Odual	421,819	70,303	32
	Ahoada East	248,428	41,404	19
	Ahoda West	37,226	62,044	28
	Andoni	325,500	54,250	25
	Asari - Toru	328,283	54,714	25
	Bonny	321,108	53,518	24
	Degama	372,614	62,102	28
	Eleme	284,081	47,346	21
	Emuoha	300,307	50,051	23
	Khana	437,524	72,921	33
	Obio/Akpor	690,585	115,097	52

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	Opobo/Nkoro	228,278	38,046	17
	Tai	179,697	29,949	14
Delta	Bomadi	125,527	20,921	9
	Burutu	303,509	50,585	23
	Ethiope East	293,243	48,874	22
	Ethiope West	295,826	49,304	22
	Isoko North	209,501	34,917	16
	Isoko South	343,159	57,193	26
	Ndokwa East	150,639	25,106	11
	Ndokwa West	218,936	36,489	17
	Okpe	187,376	31,229	14
	Oshimili North	172,990	28,831	13
	Oshimili South	218,948	36,491	17
	Patani	98,346	16,391	7
	Sapele	254,323	42,387	19
	Ughelli North	467,991	77,999	35
	Ughelli South	310,311	51,719	23
	Ukwuani	173,711	28,951	13
	Warri North	198,688	33,115	15
	Warri South	455,270	75,878	34
	Warri South-West	170,069	28,345	13
		10,047,924	**1,729,487**	**800**

Source: National Population Commission (2006)

Methods of data collection

Structured questionnaire copies were personally administered to the target population with the help of seven trained field assistants. After the purpose of the survey had been explained to the respective respondents and consent for the survey was given, copies of questionnaire were administered to the respondents. To avoid questionnaire loss, respondents were convinced to instantly respond to the questions. For quality assurance, the completed and returned copies of the questionnaire were carefully preserved to avoid loss and destruction. Of the total of 800 copies of questionnaire administratered 653 copies were retrieved and out of which 632 copies were used for the analysis. The remaining copies were voided for double entries.

Methods of data analysis

Data obtained from the administered questionnaire were analyzed using simple percentages, and logistic regression analysis. Data transformation into dummies of 1 and 0 was carried out on some items to make them data appropriate for the application parametric test (Alkharusi, 2012; Deinne and Ajayi, 2017) such as multiple regression analysis and PCA. Therefore, positive responses were assigned the value 1, and negative 0. For instance, education was recoded into primary/secondary school as 1 and otherwise as 0; occupation was recoded into working (employed) as 1 and otherwise as 0 and so on. Also, items measured on Likert Scale with responses ranging from strong agree to strong disagree were recoded into dummies of 1 for Agree and 0 for disagree. Thus, responses of strongly agree and agree were taken as 1, and others as 0 (strongly disagree and disagree). Statistical analyses were performed using Statistical Package for Social Sciences (SPSS) Version (22.0) for Windows and excel spreadsheet.

3. Results

Socioeconomic characteristics of respondents

The sex of respondents showed that males dominated the survey. The age of respondents showed that across the selected states, respondents within the ages of 21 – 60yrs dominated the survey (86.2%), followed by those above 7.4 years old, while those <20yrs had the lowest proportion of respondents of 6.3%. The general pattern therefore shows that majority of the respondents (93.7%) fall within the ages of 21 years and above. It means therefore that the age of respondents residing in coastal communities is predominantly dominated by adults. Similar age pattern of 31yrs and above was reported among riverine communities by Samuel et al., (2017) in Kogi State. Marital status of the respondents showed that a larger percentage was married followed by those who were unmarried. The educational status revealed that a significant proportion (40.5%) of the respondents had primary education, followed closely by secondary education and tertiary education with 39.2 and 20.3% respectively.

The monthly income of respondents showed that a good number (57.8%) of the respondents earned <₦18, 000 monthly, followed closely by those that earned ₦19, 000 - ₦40, 000 per month, and 10.3% earned ₦41, 000 - ₦80, 000monthly; 5.5% earned ₦81, 000 - ₦120, 000monthly; 3.8% earned ₦121, 000 - ₦150, 000monthly, while a low proportion of the respondents earned >₦150, 000 per month. The general pattern of income therefore implies a significant proportion earn <₦18, 000 - ₦80, 000 monthly suggesting that the area is predominantly occupied by low-income earners. Similar result among riverine communities in Kogi State was reported by Samuel et al., (2017); the study reported that 94.6% of the respondents earned ₦10, 000 - ₦50, 000 monthly. The occupation of respondents revealed that a larger percentage of the respondents (47.6%) were unemployed; 14.4% were involved in petty trading, farming, artisans and other menial jobs to make ends meet; 13.8% were not ready to work or seek for employment; 13.9% were employed though on part-time, while 10.3% were fully employed.

Influence of socioeconomic factors on household exposure to flood

The effect of socioeconomic factors (sex, age, education, occupation and monthly income) on household exposure to flood is presented in Table 2. This was achieved using logistic regression analysis. In the analysis, the independent variables were sex, age, education, occupation and monthly income, while household exposure to flood was the dependent variable. Data for the independent variables were obtained from Section A of the questionnaire, while data on household exposure to flood was obtained using the flood exposure option that says *people in my community have been living on the floodplain for a long time;* this item was chosen to represent household exposure to flood because it had the highest mean response. The dependent and independent variables were transformed into dummies of 1 and 0. Similar approach was employed by Ashraf et al., (2015). The result obtained is shown in Table 2. The result revealed that the logistic regression using the Forward Wald approach (similar to stepwise regression) produced three models that significantly predicted household exposure flood.

In the first model, only occupation (X^2 = 39.186, p<0.05) was retained to significantly predicted household exposure flood and it explained only 10.8% of the variation in the dependent variable. However, in the second model, with the addition of occupation, the level of explanation increased to

11.9%. In the third model, the level of explanation increased with the inclusion of marital status and it showed that sex, marital status and occupation explained 13.2% of the variation in household exposure flood. The third model was therefore used for explanation of the impact of socioeconomic factors on household exposure flood; and it revealed that sex (X^2=6.467, p<0.05), marital status (X^2=4.861, p<0.05) and occupation (X^2=41.428, p<0.05) significantly predicted household exposure to flood. Other predictor variables were excluded from the model because they did not contribute significantly to the prediction of household adaptive capacity to flood (p>0.05).

Furthermore, the Exp (B) column indicated that occupation (4.74) and sex (2.01) had *odd ratio (OR)* greater 1 which meant that occupation and sex were at least more one times more likely to predict household exposure to flood. Using the Odd ratios of the significant socioeconomic factors, it is apparent that occupation has the highest likelihood to predict household exposure to flood, followed closely by sex; it therefore means that occupation contributes most to household exposure to flood. The occupation of respondents in the area explains their income level; this is because people in high placed positions in the society tend to earn more than those in low positions. As it could be fathomed out from the occupational status of respondents, majority is unemployed and engaged in petty trading and by implication it suggests low economic status. This people tend to live in flood prone areas due to the low rental cost and low land value. As such, they are unable to reduce their level of exposure to flood by avoiding risky areas. By accepting to live in flood prone areas, such people or households are frequently exposed to flood. This lends support to the findings of Kawasakia et al., (2020) where a good number of people living in flood prone area are poor with low income status. The result in Table 2 therefore identifies occupation and sex to significantly predict household exposure to flood with occupation having higher predictability. Seekao and Pharino (2016) found poverty and limited access to financial resources to affect people's ability to combat flooding events.

Table 2: Summary of logistic regression result showing influence of socioeconomic factors on household exposure to flood

Models	Variables	B	S.E.	Wald	Df	Sig.	Exp(B) Odd ratio
Step 1	Occupation	1.478	.236	39.186*	1	.000	4.384
	Constant	-2.291	.158	209.757	1	.000	0.101
Step 2	Sex	.616	.269	5.231*	1	.022	1.852
	Occupation	1.496	.238	39.560*	1	.000	4.465

	Constant	-2.730	.260	110.547	1	.000	0.065
Step 3							
	Sex	.696	.274	6.467*	1	.011	2.005
	Marital status	-.534	.242	4.861*	1	.027	0.586
	Occupation	1.555	.242	41.428*	1	.000	4.736
	Constant	-2.545	.270	88.820	1	.000	0.078

Overall model estimation

Chi-square	df	Sig.
4.932*	1	0.026
48.786*	3	0.000
48.786*	3	0.000

Nagelkerke R Square = 0.132; *Significant at 5% confidence level

Influence of Socioeconomic Factors on Household Adaptive Capacity to Flood

The influence of socioeconomic factors on household adaptive capacity to flood was also determined (Table 3). In the analysis, the independent variables were sex, age, education, occupation, years of residence and monthly income, while household adaptive capacity to flood was the dependent variable. Data for the independent variables were obtained from Section A of the questionnaire, while data on household adaptive capacity to flood was obtained using the adaptive capacity option that says *People in my community have adaptive capacity to recover from flood;* this item was chosen to represent adaptive capacity because it had the highest mean response. The result obtained is shown in Table 3. The result revealed that the logistic regression using the Forward Wald approach produced two models that significantly predicted household adaptive capacity to flood.

In the first model, only occupation (X^2 = 45.253, p<0.05) was retained to significantly predicted household adaptive capacity to flood and it explained only 9.8% of the variation in the dependent variables. However, in the second model, with the addition of monthly income, the level of explanation increased to 11.9%. The second model was therefore used for explanation of the impact of socioeconomic factors on household adaptive capacity to flood because it gives a better explanation. The result therefore shows that occupation(X^2=33.566, p<0.05) and monthly income (X^2=10.648, p<0.05) significantly predicted household adaptive capacity to flood. Other predictor variables were excluded from the model because they did not contribute significantly to the prediction of household adaptive capacity to flood (p>0.05).

The result of *Odd Ratio (OR)* indicated that occupation (0.314) had *OR* less than 1, while monthly income (1.000) had Odd ratio of 1 (Table 3). This means that monthly income was at least one times likely to predict household adaptive capacity to flood. Using the Odd ratios of the significant socioeconomic factors, it is apparent that monthly income has the highest likelihood to predict household adaptive capacity to flood; it therefore means that monthly income contributes most to household adaptive capacity to flood. Monthly income is therefore identified as the principal socioeconomic factor that significantly influences household adaptive capacity to flood. This is expected as household income to a large extent determines people's extent of response to flood. When people in an area earn high monthly, they will be able to come together (levy themselves) to confront any environmental issue of dire concern to them.

And at individual level, households with high income will not build houses in flood prone areas and if they wish to, they make sure the right building materials are used and all the necessary preventive measures are put in place. The result in Table 2 therefore recognizes monthly income to significantly predict household adaptive capacity to flood. This result is consistent with the findings of earlier and related studies. For instance, Adelekan (2016) reported high-income households to have the adaptive capacity to flood. The study stated that in a high-income residential area along flood prone areas, households levied themselves at a high cost to procure boulders to protect their environment from storm surges. Similarly, Seekao and Pharino (2016) found poverty and limited access to financial resources as major constraints affecting the adaptive capacity to combat future flooding events. The study of Ahmad and Afzal (2020) found limited income, inadequate planning for land use, lack of advanced and early warning system, and inadequate sound financial status to affect households' level of adaptation of mitigation strategies. Also, Thanvisitthpon et al., (2020) found economic resources and infrastructure component to significantly influence the adaptive capacity of Phetchaburi municipality in Thailand to flooding.

Table 3: Summary of logistic regression result showing influence of socioeconomic factors on household adaptive capacity

Models	Variables	B	S.E.	Wald	df	Sig.	Exp(B) Odd Ratio
Model 1	Occupation	-1.308	0.194	45.253*	1	0.000	0.270
	Constant	1.164	0.107	117.637*	1	0.000	3.202
Model 2	Occupation	-1.159	0.200	33.566*	1	0.000	0.314

Average income	0.000	0.000	10.648*	1	0.001	1.000
Constant	1.436	0.139	106.142*	1	0.000	4.205

Overall model estimation

Chi-square	Df	Sig.
10.379*	1	.001
56.028*	2	.000
56.028*	2	.000

Nagelkerke R Square = 0.119; *Significant at 5% confidence level

Assessment of Household Economic and Social Capacity to Flood

This part assesses households' ability to manage flooding in their respective environments and result obtained is shown in Table 4. On the question that *People in my community have strong economic status*, the result revealed that extremely low economic status; this is affirmed by the responses where majority of the respondents stated that people in their respective communities do not have strong economic status. This again agrees with the income and occupational statuses of households in the area. The low economic status of households across the states shows their inability to adequately combat flood which makes it a recurrent environmental problem. On the extent of poverty, the result showed that a significant percentage of households in Rivers and Bayelsa States are poor and this by extension implies decrease in adaptive capacity to combat flood and increase exposure to flood. In Delta State, the poverty level is relatively better compared to the other states with a substantial number of households not poor; which by extension suggests improved adaptive capacity to flooding. However, looking at the general pattern, it is apparent that because households across the states are poor, they are unable to combat flooding. It shows therefore that majority of the households are poor. The general economic implication of the responses obtained suggests that households or people in the studied locations do not have the requisite economic resources or capacity to adequately deal with the recurrent flooding events. This is because to adequately avoid or manage flood, households or communities have to develop or pay for projects involving structural defenses (e.g., dams. levees, retention basins) and non-structural measures (e.g., land-planning, insurance, forecasting). These investments according to Grames et al., (2016) are costly, but able to avoid the devastating impacts of flood.

Table 4: Household perception of economic and social capacity to flood

	States

Variables	Categories	Rivers (%)		Delta (%)		Bayelsa (%)	
		A	D	A	D	A	D
Economic status	People in my community have strong economic status	23.8	74.4	14.6	81.2	27.4	69.4
	Many people in my community are poor	79.8	18.4	46.5	51.5	61.0	34.4
	My community has diverse sources of income and supplementary livelihoods others	42.6	54.9	13.4	75.0	37.9	56.8
Social status	My community has the resources it needs to take care of community problems	15.9	82.3	5.8	90.8	10.5	88.5
	My community gets financial flood support	23.1	76.9	4.2	91.9	14.8	83.2

A = Agree (SA+A); D = (SD +D); the remaining percentage represents undecided

On the social aspect, the result presented in Table 4 showed that households across the studied locations do not have the resources needed to take care of environmental problems. It goes to show that the locations do not have in place the information, technology, tools and services to manage the social aspect of flooding. As expected as across the locations, early warning systems and other necessary gadgets that enable flood related information to be communicated to the people are not available. This immensely undermines community's effort to avoid flood. The second aspect of social capacity showed that households in the studied locations do not have financial flood support. What this implies is that households do not come together to devise ways of managing flood. They do not maintain cordial relationship and link to work together as one family to effectively deal with flood incidence. The general result therefore means that households across the selected locations lack or do not have the social capacity for flood management. In line with this, Hudson et al., (2020) stated that adaptation to flooding requires sufficient social capital (in terms of linkages between members of society) and risk perceptions (understanding of risk) to be effective. The study found a positive relationship social capital, risk perceptions, and self-efficacy to the likelihood of successful adaptation to flood. In the present study, the generally low social capacity among households shows the absence of linkages in flood adaptation. Social capacity or capital is simply the relationships and bond that exist between people within and beyond their communities for flood adaptation (Norris et al., 2009).

4. Conclusion

The study has shown that households in the study locations have low financial base which exposes them to flood and also affects their adaptive capacity to flood. The adaptive capacity of households to flood in the study locations is observed to be significantly influenced by their monthly income. This is expected because households with high monthly income have higher adaptive capacity than those with low monthly income. This is because those with high income are able to put in place flood protection measures. Also, they are able to buy lands and build houses in areas that are not prone to flooding. This puts them far above those with low income who are unable to afford three square meals not to talk of flood protection measures. The generally low financial base of households in the area could be said has tremendous impact on their exposure to flood, susceptibility to flood as well as adaptive capacity to flood. This is expected because household extent of social vulnerability is income dependent.

The study further reveals that households in the studied locations do not have the requisite economic and social capacity to adequately deal with and adapt to flooding. In order to reduce household level of exposure to flood and improve their adaptive capacity to flood, the study suggests that government and private individuals should be encouraged to increase the adaptive capacity of flood prone communities by putting in place structural adaptive measures. These measures could include the construction of drainage channels, placement of breakwater along part of the coast and demolition of buildings in some high flood prone areas among others. Such assistance is needed as a result of the low financial base of households in the study locations.

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