International Journal of Disaster Risk Reduction 60 (2021) 102310

Contents lists available at ScienceDirect

International Journal of Disaster Risk Reduction

journal homepage: www.elsevier.com/locate/ijdrr

Implications of the drivers on the selection of flood coping strategies in Jigawa State, Nigeria?

Abdulmalik M. Yusuf [a,b], Yusuf Isah Maikudi [a,b], William Adzawla [c,*]

[a] WASCAL Climate Change Economics, Cheikh Anta Diop University, Dakar, Senegal
[b] Department of Economics, Ahmadu Bello University, Zaria, Nigeria
[c] International Fertilizer Development Center, PMB CT 284, Cantoments, Accra, Ghana

ARTICLE INFO

Keywords:
Coping strategies
Floods
Nigeria
Resilience
Vulnerability

ABSTRACT

Despite efforts by the Nigerian government to improve on flood infrastructure, the yearly incidences of floods have remained unabated and put households under threats. This study examined the factors that determine households' (flood victims) choice of flood coping strategies in the Jigawa State, Nigeria. Although some of the strategies can also be considered as flood mitigation strategies, the emphasis is on coping strategies. The study used survey data from 251 randomly selected households (flood victims of 2016) and the data was analysed using multivariate probit and random forest models. The results show that factors such as sex, age, education, occupation, income, housing status, flood education and location in specific local government areas are significant in determining households' choice of flood coping strategies. Among the flood coping strategies analysed, access to credit from banks, seeking government's support and access to early warning information systems are crucial. The findings led to the conclusion that policies and programmes designed to manage and reduce flood risks must take into account the input of all relevant stakeholders, particularly the different age and income groups. The study also recommends the need for institutions in charge of flood disaster risk reduction and management to focus more on investing in non-structural measures of flood control to improve households resilience to floods.

1. Introduction

In recent decades, the world has witnessed environmental challenges resulting from the effect of industrialization, economic development, population growth, urbanization and changing lifestyles [1]. Coupled with these, global warming or climate change constitutes one of the greatest challenges faced in the 21st century and has become a defining challenge for policy makers, civil society organizations and industries. Among climate and weather-related events, flood disasters are reportedly on the rise, negatively affecting poor people and limit the potentials of urban development [1]. These challenges are expected to be aggravated by associated climate-related risks and natural hazards. There is high concentration of people and economic assets or activities in cities, and mostly, these cities are located in coastal areas. This makes them vulnerable to weather risks and natural hazards. Hence, floods, drought, earthquakes, sea level rise and storm surge will have varied and increasing impacts on urban areas [2–4].

Historical data has shown that between 2000 and 2010, floods has occured most (1501 times) among climate-related events and natural disasters, followed by storms and cyclones (899 times), and earthquakes (228 times) [3]. Other climate risks were extreme temperature (173 times), mass movements (167 times), droughts (133 times), wildfire (101), volcanoes (53 times), storm surge (29 times) and tsunamis (19 times) [3]. This is shown in Fig. 1. Thus, flooding is the greatest natural and climate-related threats to human existence, and those living in informal settlements will constitute the most vulnerable group. These categories of individuals live in low-income neighbourhoods characterized by a lack of or inadequate infrastructure (drainage, sewers, roads, etc.) and social services (health care, housing, nutrition, etc). These living conditions could sometimes explain why natural hazards could lead to disasters involving loss of lives, destruction of houses, spread of vector and water-related diseases, and loss of means of livelihoods [5–7].

Out of about 27.8 million global new displacements from 127 countries in 2015, 19.2 million of them were linked with disasters in 113 countries. In Africa, the major factors responsible for displacement include droughts, floods, communal and political conflicts, storms and other natural disasters. In 2015, Africa was home to over 15 million

* Corresponding author.
E-mail address: adzawlawilliam@gmail.com (W. Adzawla).

https://doi.org/10.1016/j.ijdrr.2021.102310
Received 2 February 2021; Received in revised form 23 April 2021; Accepted 1 May 2021

internally displaced persons (IDP). These displacements have impacted negatively on the environment by contributing to increased environmental degradation, and also puts serious pressure on scarce food, water, and energy resources. Hence, there is the need for collective humanitarian and development initiatives to address the root causes of forced displacements and mitigate its impacts on the environment [8].

Existing studies on floods in Nigeria, particularly those that have looked at vulnerabilities and flood disaster risk management efforts include impacts and institutional responses to floods [7], factors responsible for reoccurrence of floods in some Nigerian cities and flood effects on human activities [9], gender and urban/rural differences in the impact of floods [10] and factors influencing households' and individuals' adaptive capacity to flood disasters [11]. Some flood management and risk response studies in Nigeria have recommended the need for building flood resilient infrastructure through restructuring cities, a call that require the participation of all stakeholders [7,12]. Despite this call, there is no research to examine the factors influencing households' (flood victims) choice of coping strategies to flooding in Nigeria. This may hinder the design of appropriate policies to build the resilience of households to floods. Therefore, this research is important as it provides insight on ways to help reduce households' vulnerability to flood in high-risk flood areas. This study focused on Jigawa State of Nigeria and addressed these literature gaps.

2. Literature review

Flood is a crucial component in the climate system, with unparalleled historical occurrences. This has sparked significant discussion among climate change researchers and policy makers. The effective management of flood risks has been a decisive issue over the years. There are also economic implications of flood occurrences [13,14]. For instance, evidence indicate that flood disasters have cost billions of dollars over the past decades, resulted in thousands of deaths and caused psychological issues such as depression and anxiety, as well as several injuries [15–17].

In some Sub-Saharan African countries such as Nigeria, flood disasters have resulted in dislodgments of houses and properties [18]. As a result, Nigeria's losses have amounted to billions of dollars [19]. These dislodgements has also resulted in homelessness, transmission of widespread infections and diseases, and as well as famine [20,21]. These disasters are commonly connected to global climatic change as well as inadequate regional planning of areas susceptible to flood [22,23].

Nigeria had a widespread flooding incident in 2012 that affected approximately 32 States and was the worst on record with several days of heavy downpours in some of these states [19] report). The floods extended from July to October that year and affected 7.7 million people, of which over 2 million were recorded as internally displaced persons (IDPs). In the past, flooding in Nigeria was typically fluvial, coastal, and pluvial in nature and had mostly affected rural areas and country sides [24]; and [25]. The fluvial floods would usually result from the major flood pressure witnessed in areas with major rivers that cuts across the North-western, Middle belt and South-south regions of the country [26]. Nonetheless, flood can be mitigated because these incidences are predictable. Mitigation can be done using best practices in flood risk reduction and the lessons learned from other countries' experiences. But the efforts of stakeholders in disaster management have been limited mainly due to lack of quality data [27].

Analytical frameworks on adaptive capacity mostly hinges around discussions on the concept of vulnerability and resilience. In other words, the more vulnerable individuals, households, communities or countries are to disasters (i.e., floods in this case), the lower their adaptive capacity and vice versa [10]. The concept of adaptive capacity can be better understood through its dynamic features such as the availability of robust resources for use (robustness), the extent of substitutability of elements (redundancy) and how rapid one can access resources for use (rapidity). These attributes are very important in understanding the meaning of adaptive capacities of entities [28]. As defined by IPCC, "resilience is the capacity of social, economic and environmental systems to cope with hazardous events, trends or disturbances, responding or reorganizing in ways that maintain their essential functions, identity, and structure, while also maintaining the capacity for adaptation, learning and transformation" [4]. Vulnerability on the other hand is the degree of damage or destruction that should be anticipated under any given conditions of exposure, susceptibility and resilience. To frame the explanation within the context of floods, a system is said to be 'susceptible' to floods as a result of 'exposure', combined with the ability/inability to cope, to adapt, to recover, and to be resilient. For example, it is possible to find some structural and non-structural measures in place that promote resilience to protect an initially exposed population from an imminent flooding situation [29]. Conversely, there are also exposed population with weak or even no flood defences, who are more prone to flooding and subjected to greater

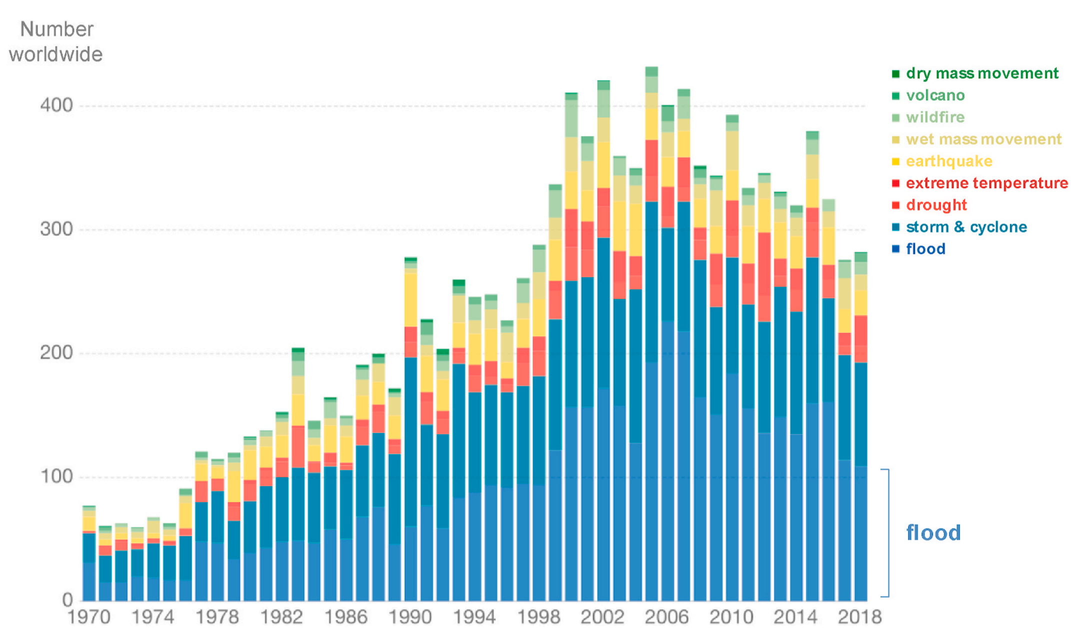

Fig. 1. Distribution of natural disasters worldwide (source: Our world in data, 2018).

life threats and economic losses [30]. Researchers also see vulnerability as the outcome from the interactions between the three indicators: exposure, susceptibility, and resilience. In measuring disaster resilience, several variables grouped into infrastructural (housing type and access medical services), institutional (social networks, mitigation interventions and provision of municipal services), social (age, education equity and access to transportation services) and economic (employment opportunities, reliance on single sector employment and housing capital) have been identified. Also, community capital which encompasses innovations and political engagements influence the resilience of communities. In addition to using composite resilience scores, Cutter's study provided a spatial description for each of the categories of disaster resilience considered [31].

Moench & Dixit [32] in a related study on floods which combined recommendations from the review of other studies itemized eight (8) main determinants of vulnerability and adaptive capacity to disasters. These factors include the types of livelihood options in a region and the ability to pursue diversification, the ability to access non-agricultural income sources via migration, available flow of resources and information services in and out of an affected region, availability and access to social infrastructure (e.g., social networks, NGOs and banks), established patterns of vulnerability, the type and nature of available physical infrastructure and the extent of their vulnerability as well as their ability to ensure livelihood sustenance, the extent of access to hygienic sources of water by households and the state of natural resources in relation to the way water surface systems have been distorted. Furthermore, they observed that while individuals and household have the ability to develop their adaptive capacity based on their disaster experiences, adaptive strategies are developed via partnerships with international and local agencies. Others like Rawadee & Areeya [33] in their description of the indicators of adaptive capacity categorized it into five (5): infrastructure (i.e., housing tenure, nature and composition of a building in terms of materials used for its construction and availability of basic social amenities such as electricity and pipe borne water), economic (the amount of income sources available), technology (availability of convenience items such as internet, television, vehicles and radio), social capital (efficiency of community networks) and, skills and knowledge (in terms of interpretation of early warning systems and applying indigenous knowledge on flood mitigation). Cutter et al. [34] also itemized the factors influencing social vulnerability to environmental hazards to include zero access to resources (like technology, knowledge and information), social capital (such as social connections and networks), building stock and age as well as the nature and amount of infrastructure lifelines available. From the above submission, one can observe convergence in the ideas of the authors in areas such as infrastructure, skills and knowledge, and income diversification, all of which constitute factors determining adaptive capacity. It is important to note however, that the observed differential impacts of disasters on various groups explains the different range of factors affecting adaptive capacities of individuals, households and regions as identified among the vast available literature on this subject matter.

3. Methodology

3.1. Study area

Jigawa State is in the North-western region of Nigeria on latitude 12.00^{o}N and longitude 09.45^{o}E) (Fig. 2). Its capital is Dutse. Jigawa State has a total of 27 Local Government Areas (LGAs). The State covers a landmass of about 24,742 km^2, with a population of around 5,828,200 people in 2016 [35]; NBS, 2016). About 14% of the total landmass of Jigawa State are wetland (Fadama).

The State occupy mainly Sudan Savannah vegetation and Sahel Savannah vegetation types [36], with a combination of tropical wet and dry climates (with seasonal rainfall between May and October). The city experiences a mean annual temperature of about 30 °C. Rainfall variability is pronounced and its distribution is skewed, with an annual average between 635 mm to 899 mm [37].

Jigawa State has a rural and urban population of 85% and 15%, respectively. At least 80% of Jigawa's landmass is arable. As such, the primary occupation is agriculture. The major causes of frequent flooding in the area include heavy and prolonged rainfalls associated with storms, inadequate drainage facilities, mismanagement of dams and reservoirs located outside Jigawa State, infiltration of river/water pathways by weeds, topography of the area, and vegetation of the area. Aggregate information on losses due to floods for three States (Jigawa, Kebbi and Sokoto State) showed that there are about 40 deaths, with a total of 1,500,200 people affected by floods. There are many other properties including houses that are destroyed by floods. Dartmouth Flood Observatory (2016) estimated a total loss of about US$ 30 million due to the impacts of floods on the State.

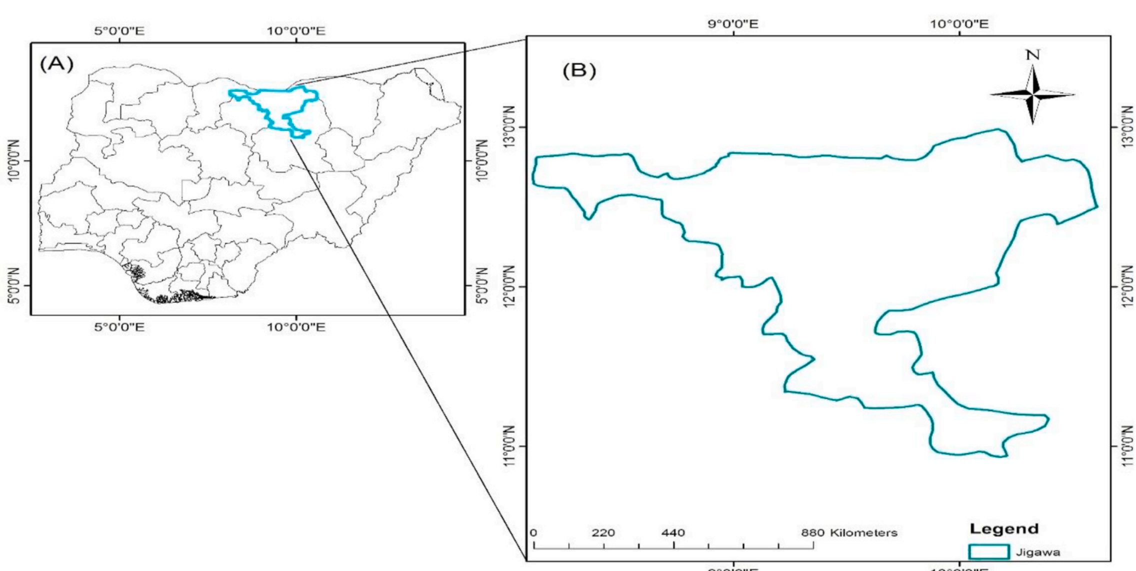

Fig. 2. Location of Jigawa State on the map of Nigeria (Source: Author's Construct).

3.2. Data and sample

Both primary and secondary data were used for this study. The secondary data were obtained from the Nigerian Meteorological Agency (NIMET) and the Nigerian National Emergency Management Agency (NEMA). The primary data (cross-sectional) were collected from households through survey interviews. Key informant interviews were conducted with the Ministry of Housing and Urban Planning, Ministry of Environment officials, as well as those in NEMA. The use of different data sources ensured proper triangulation of the results.

Based on the data obtained from NEMA on 2016 flood statistics, a total of 9459 households (sample frame) in Jigawa State were affected by floods in 2016. From a 95% confidence interval with a margin error of 5%, a sample size of 370 household heads were selected through survey monkey calculator for sample size determination. Available data also show that a total of nine LGAs (Babura, Malam Madori, Hadejia, Kafin Hausa, Ringim, Jahun, Guri, Dutse and Suletankarkar) are affected by the floods in 2016. Therefore, the study randomly selected four out of these nine LGAs. The selected LGAs are Ringim (Ringim, Majiya Gari and Auramo Sabuwa communities), Guri (Guri and GRA communities), Hadejia (Hadejia and Gudiccin communities), and Kafin Hausa (Tage community). The questionnaires were randomly distributed among male and female household heads across the eight communities within the four selected LGAs. Table 1 shows the study population and sample per the four LGAs. This indicates that only 251 household heads responded completely to the questionnaires administered (a 67.8% response rate). Hence, our analysis was based on the 251 households that were interviewed between December 2017 and February 2018.

3.3. Multivariate probability model

Households have the option of choosing one or more coping strategies at the same time. In order to estimate factors (such as socio-economic and behavioural characteristics) that influence households' decision under each flood coping strategy, the multivariate probability regression model offers the appropriate estimation method. This is because the technique allows one to estimate choices involving the simultaneous selection of more than one flood coping strategy and addresses the collinearity in the coping strategies. As such, the method helps to understand the mechanism behind the collective decision-making processes by the households [39].

The procedure for developing the multivariate probability model involves applying an extension to bivariate probability model to handle the covariance, where more than two binary response variables are involved [40]. In a bivariate procedure, assuming households affected by flooding obtained bank credit and/or relied-on government's supports as two coping strategies, then the factors influencing the decision to choose any or both coping strategies is autonomous. Hence, two simultaneous binary probability models must be estimated. Just like in the case of a univariate probability model, the bivariate probability model states that [40]:

$$y_1^* = X_1^*\beta_1 + \varepsilon_1, y_1 = 1 if y_1^* > 0, and 0 if otherwise \quad (1)$$

Table 1
Distribution of sample size according to population profile.

Selected LGAs	No. of HH affected	Distribution of sample size	No. of response
1. Ringim	1525	164	106
2. Guri	822	88	61
3. Hadejia	525	57	48
4. Kafin-Hausa	570	61	36
Total	**3442**	**370**	**251**

Source: Author's computation based on NEMA [38] data.

$$y_2^* = X_2^*\beta_2 + \varepsilon_2, y_2 = 1 if y_2^* > 0, and 0 if otherwise \quad (2)$$

Hence:

$$\left(\begin{matrix}\varepsilon_1\\ \varepsilon_2\end{matrix}\middle| X_1, X_2\right) \sim N\left[\begin{matrix}0\\0\end{matrix}, \begin{pmatrix}1 & \rho\\ \rho & 1\end{pmatrix}\right] \quad (3)$$

Equation 3 implies that:

$$E[\varepsilon_1|\mathrm{X}_1,\mathrm{X}_2] = E[\varepsilon_2|\mathrm{X}_1,\mathrm{X}_2] = 0$$

$$Var[\varepsilon_1|\mathrm{X}_1,\mathrm{X}_2] = Var[\varepsilon_2|\mathrm{X}_1,\mathrm{X}_2] = 1$$

$$Cov[\varepsilon_1,\varepsilon_2|\mathrm{X}_1,\mathrm{X}_2] = \rho$$

Based on maximum likelihood estimation procedure, the bivariate normal cumulative distribution function (CDF) can be defined as:

$$\mathrm{Prob}(X_1 < x_1, X_2 < x_2) = \int_{-\infty}^{x_2}\int_{-\infty}^{x_1} \phi_2(z_1, z_2, \rho)dz_1dz_2 = \Phi_2(x_1, x_2, \rho) \quad (4)$$

Hence, it follows that the density function would be:

$$\Phi_2(x_1, x_2, \rho) = \frac{e^{-\left(\frac{1}{2}\right)\left(x_1^2+x_2^2-2\rho x_1x_2\right) \Big/ \left(1-\rho^2\right)}}{2\pi(1-\rho^2)^{\frac{1}{2}}} \quad (5)$$

To derive the log-likelihood, the following notations are used:

$$q_{i1} = 2y_{i1} - 1$$
$$q_{i2} = 2y_{i2} - 1$$

Thus, $q_{ij} = 1$ *if* $y_{1j} = 1$ *and* -1 *if* $y_{1j} = 0$; $j = 1, 2.$, given that $z_{ij} = X'_{ij}\beta_j$, $w_{ij} = q_{ij}z_{ij}$ *and* $\rho_{i*} = q_{i1}q_{i2}\rho.$

The bivariate normal distribution of the density ϕ_2 and Φ_2 is indicated by the subscript 2. In this case, the probabilities enter the likelihood functions as:

$\mathrm{Prob}(Y_1 = y_{i1}, Y_2 = y_{i2}|\mathrm{X}_1,\mathrm{X}_2) = \Phi_2(w_{i1}, w_{i2}, \rho_{i*})$. The log-likelihood function is expressed as $InL = \sum_{i=1}^{n} In\Phi_2(w_{i1}, w_{i2}, \rho_{i*})$. After obtaining the maximum likelihood estimates, we can then obtain the partial or marginal effects by evaluating the equation below:

$$\mathrm{Prob}(Y_1 = 1, Y_2 = 1|X) = \Phi_2(x'\gamma_1, x'\gamma_2, \rho) \quad (6)$$

A change in X can be expressed as:

$$\frac{\partial\Phi_2}{\partial X} = g_1\gamma_1 + g_2\gamma_2$$

This bivariate information can be extended to the multivariate probability model as:

$$y_m^* = X_m^*\beta_m + \varepsilon_m, y_m = 1 if y_m^* > 0, and 0\ if otherwise, m = 1, ..., M$$

where:

$$E[\varepsilon_{\mathrm{m}}|\mathrm{X}m....\mathrm{X}_{\mathrm{m}}] = 0$$
$$Var[\varepsilon_{\mathrm{m}}|\mathrm{X}_{\mathrm{m}}...\mathrm{X}_{\mathrm{m}}] = 1$$
$$Cov[\varepsilon_{\mathrm{m}}...\varepsilon_{\mathrm{m}}|\mathrm{X}_1...\mathrm{X}_{\mathrm{m}}] = \rho_{jm}$$
$$(\varepsilon_{\mathrm{m}}...\varepsilon_{\mathrm{m}}) \sim N_m(0, \Re)$$

Finally, the log-likelihood function becomes:$L_{\mathrm{m}} = \Phi_{\mathrm{m}}(\mathrm{q}_{i1}X'_{i1}\beta_1, ..., \mathrm{q}_{im}X'_{im}\beta_m, \Re^*)...\varepsilon_{\mathrm{m}}$, where $\mathrm{q}_{im} = 2y'_{im} - 1$and. $\Re^*_{jm} = q_{ij}q_{im}\rho_{jm}$

The variables considered in the multivariate probit regression is shown in Table 2.

3.4. Random forest model (RFM)

The random forest model (RFM), also known as random decision trees, is a data mining technique which is mainly used for classification and regression analysis. In other words, decision trees (in a forest form) form the building block of the random forest model. For example, predicting the maximum temperature today requires taking into account

Table 2
List of variables and definitions.

Variable	Definition and measurement
Origin	Dummy: 1 if household head is located in their original home local government area, 0 if not.
Guri	Dummy: 1 if household head is located in Guri local government area, 0 if otherwise.
Hadeja	Dummy: 1 if household head is located in Hadeja local government area, 0 if otherwise.
Kafin Hausa	Dummy: 1 if household head is located in Kafin Hausa local government area, 0 if otherwise.
Sex	Dummy: 1 if household head is a male and 0 if a female
Age	The total number of years from birth of a household head.
Family size	The total number of nuclear household members of a household head
Marital status	Dummy: 1 if household head stays with spouse(s) and 0 if otherwise.
Education	The total number of years of formal education of a household head.
Occupation	Dummy: 1 if the primary occupation of a household head is non-farm and 0 if main occupation is farming.
Agric income	The total amount of income from agricultural activities in a year (Naira)
Non-agric. income	The total amount of income from non-agricultural activities in a year (Naira)
House status	Dummy: 1 if household head lives in own residence and 0 if otherwise.
OSC	Dummy: 1 if the household head is located in an area with Open Sewage or Canal
SEA	Dummy: 1 if household is situated in an Elevated Area (HSEA), and 0 if otherwise.
ALFHA	Dummy: 1 if household head is Aware of Location in Flood Hazard Area (ALFHA) hence and of high flood risk, and 0 if otherwise.
LERG	Dummy: 1 if there is a Local Emergency Response Group (LERG) in the community of the household head and 0 if otherwise.
AFRP	Dummy: 1 if household head is aware of flood related program (AFRP) in the local government area and 0 if otherwise.
EFWSC	Dummy: 1 if household head is located in a community where there is an early flood warning system in the community (EFWSC) and 0 if otherwise.

Source: Author's construct

many factors, including information on past and present weather behaviour. To Breiman [41], random forests involve significant alteration of bagging to form a huge collection of uncorrelated trees, which are then averaged [42]. The problem arises from the diversity in knowledge that people have, as different people will normally provide different answers to the same question. The larger the sample of respondent, the more varied their predictions. Hence, using a single decision tree will likely bring complications in the prediction of the maximum temperature. This usually gives rise to the problem of overfitting, which is associated with the use of a decision tree as information increases. Theoretically, the random forest model does not suffer from having a large number of features. However, if the features included are not significant in describing the response or highly correlated, the random forest will dilute the significance of the selected features. Therefore, there is the need to remove the 'useless' features for a better interpretation of the model. By doing so, the random forest model corrects the issue of overfitting that is associated with decision trees. The aim here is to minimize the variance (errors) in the outcomes from the pooled predictions in order to arrive at right answers. The central idea behind the random forest model is the combination of many decision trees into a single model. What the random forest model does here is take a majority vote for the predicted class as in Fig. 3.

4. Results and discussion

4.1. Model diagnosis of the determinants of households' adoption of flood coping strategies

As explained in the methodology, the study estimated a multivariate probit model to determine the factors that drives the adoption of various flood coping strategies by the households. The Wald chi square of the model is 289.72, which is significant at 1%. This implies that the model sufficiently explained the variations in the adoption of flood coping strategies. Similarly, the joint correlation of the seven models shows a chi square value of 28.02, which is also significant at 5%. This implies that the error terms in the seven models are correlated hence, the estimation of a multivariate probit is justified. While the paired correlation among the models shows both positive and negative correlations, only three of the paired correlations are statistically significant (see Table 3 below). For instance, assistance from friends positively correlated with assistance from government, thus, they tend to complement each other. On the other hand, assistance from friends and relocation from a flood affected area to a safe area tend to substitute each other.

4.2. Determinants of households' adoption of flood coping strategies

This section discusses the results from the multivariate probit regression model. From Table 4, several key factors had significant effects on specific coping strategies. The respondent's sex had a positive significant effect on the decision to relocate from the current residential area to another area. This means that the male heads have a higher probability of relocating to areas that are safe to floods than female heads. This is consistent with argument that males often migrate when there is a climate shock, leaving their families behind primarily to obtain income and provide for the families that they left behind. Relatedly, Wang et al. [43] estimated that although insignificant, males have higher probability of relocating from a flood area. On the other hand and although insignificant, female heads are more likely to seek assistance from the government and friends, as well as obtain credit from banks in order to cope with floods.

Age had a positive effect on all flood coping strategies except the decision to seek assistance from the government and to relocate. However, the effect is only statistically significant for the decisions to seek assistance from friends and communal safety nets as flood coping measures. This implies that the probability of seeking assistance from friends or accessing communal safety nets is higher for the elderly than younger household heads. This is conceivable considering that as people increase in age, they might have established long-time relationship with others, hence, can have people from whom to seek assistance. At

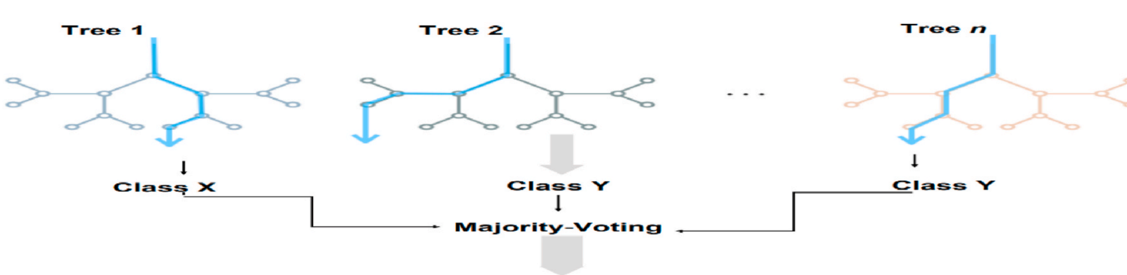

Fig. 3. A simplified random forest model (source: Author's construct).

Table 3
Correlation matrix of flood coping strategies.

X	Assistance from government	Community safety nets	Relocation	Assistance from friends	Distilling
Community safety nets	−0.159				
	(0.120)				
Relocation	−0.167	−0.205			
	(0.139)	(0.130)			
Assistance from friends	−0.162	−0.113	0.057		
	(0.111)	(0.112)	(0.107)		
Distiling	0.240**	0.131	−0.220**	0.051	
	(0.109)	(0.115)	(0.112)	(0.106)	
Credit from banks	−0.038	0.172	0.076	−0.398***	0.155
	(0.175)	(0.157)	(0.149)	(0.152)	(0.152)

Note: *, **, *** represents 10%, 5% and 1% significance level respectively.
Source: Author's computation based on field survey, 2018

Table 4
Determinants of households' choice of flood coping strategies.

Variable	Assistance from Government	Communal safety nets	Relocation	Assistance from friends	Distilling	Credit from Banks
Origin	0.225	0.411	0.732**	−0.04	−0.446	0.333
Guri	−0.543*	−1.131***	−0.850**	−0.05	−0.515**	0.306
Hadeja	1.694***	−0.042	−1.200***	−0.86***	−1.183***	−0.800**
K/Hausa	0.880**	−1.198***	−1.384***	−0.64**	−0.741	−0.020
Sex	−0.433	0.152	0.797**	−0.18	−0.037	−0.020
Age	−0.007	0.025*	−0.006	0.032**	0.020	0.032
Family size	0.063	−0.036	0.024**	−0.08*	−0.067	−0.045
Marital status	−0.078	0.062	0.365**	−0.06	0.066	0.031
Education	−0.020	-.0.084**	0.055	−0.09***	−0.035	0.114***
Occupation	0.182	0.029	−0.094	0.389*	0.307	1.130***
Agric Inc.	0.0001*	0.000	0.000	0.000	0.000	0.000
Non Agric Inc.	0.001	0.000*	0.000	0.000	0.000	0.000
Housing status	−0.013	0.049	−0.012	−0.17**	0.153*	−0.126
OSC	0.267	0.294	0.201	0.493**	0.322	−0.012
SEA	−0.207	0.411**	−0.504**	0.216	0.111	0.048
LFHA	0.225	−0.256	0.055	−0.370	0.669**	1.021*
LERG	−0.003	−0.589*	−0.745*	0.400	−0.072	0.341
AFRP	0.805***	0.385	0.037	−0.28	−0.042	0.757**
PEFWSC	0.052	−0.080	0.247	0.608	0.213	−1.415**
Constant	−0.958	−1.121	−2.793***	0.955	−0.228	−5.231***

Note: *, **, *** represents 10%, 5% and 1% significance level respectively.

community level, elders have high levels of influence in the activities of its members and also serve as entry point for external organisations. This makes it possible for them to use their influence in accessing community safety nets. Contrary to this study, Nji and Balgah [44] estimated that age have a negative relationship with the adoption of informal flood coping strategies. Cao et al. [45] also revealed that age have a negative effect on protective coping behaviours to flood disaster.

Household size had a negative effect on all flood coping strategies except for assistance from the government and relocation. However, the effect is only statistically significant for the decision to seek assistance from friends and relocation. Thus, the higher the size of the family, the lower the probability that respondent will access assistance from friends. Although the family size is not a criterion for accessing assistance from friends, the financial demand for larger households may mean that if household's income is unable to meet such demand, external funds such as those from friends can be used for domestic financing and not for the intended adoption of flood coping strategies. This is consistent with the result of Wang et al. [43]. Considering that household heads have to relocate with their family members when the decision is made, it is surprising that an increase in family size improves the probability of relocating. However, because there is resource pooling with larger households, it becomes easier for households with many of its members with much resource to relocate.

The effect of marital status on relocation is positive and statistically significant at 5%. For all other flood coping strategies, the effect was insignificant. The significant positive effect means that household heads who stays with their spouses in the same household have a higher probability of relocating from a flood area to a safe area than those who do not currently stay with their spouses or are single. Because heads staying with their spouse are more concerned of their spouse and for that matter family, they may take the decision to relocate to other areas considered safer.

Education had a significant positive effect on access to credit from banks and a negative significant effect on seeking assistance from friends and community safety nets. Thus, while respondents who had more years of formal education had higher probabilities of accessing credit from banks, the less educated were more likely to seek assistance from friends or access communal safety nets as flood coping strategies. The positive effect of education on access to credit which confirmed the result of Wang et al. [43] was expected because all processes to access credit are formal and require the applicant to read, write, and understand the credit terms and conditions. Consistently also, education generally drives people away from informal coping strategies such as seeking assistance from friends since this may have no formal terms of repayment.

The occupational status of a respondent had significant effect on access to credit and assistance from friends as flood coping strategies. In these instances, occupation had positive estimates. This implies that household heads whose current occupations are non-farming have higher probability of accessing credit from the banks, as well as obtaining assistance from friends. This is conceivable with the generally low credit disbursement and access by farmers in Nigeria.

The effects of agricultural income and non-agricultural income showed that while the former had a positive effect on seeking assistance from the government, the later had a positive significant effect on communal safety nets. Income is an important tool for enhancing adaptation/coping to climate shocks such as floods. In most agrarian communities, the high-income earners are often given or obtain higher authority in various leadership positions. Also, high income would enable the households to fund any additional financial requirement from such flood adaptation strategies. Considering that government assistance is provided by political leaders while communal safety nets are determined by the community leaders, it is plausible that an increase in income would enhance the probability to obtain assistance from governmental and communal safety nets.

The housing status of the household head had a negative significant effect on accessing financial assistance from friends and relatives, but a positive significant effect on distilling. This implies that while household heads residing in personal apartments are less likely to access financial assistance from friends and relatives, they have a higher probability of adopting distilling gutters and other chocked areas. The fact that household heads living in their own accommodation have a higher probability of adopting distilling is plausible, since they often see accommodations as their personal property, which can be affected by floods. Hence, these household heads engage in frequent distilling of open and closed gutters in their vicinity. On the other hand, household heads who reside in rented accommodations may feel that they can easily move into a different house or relocate in a different direction, making them unmotivated to engage in communal activities such as distilling.

The data shows that households with improved economic status (income and education) and relatively younger heads are located in elevated areas. For instance, the average agricultural income for those located in elevated areas is 204,136 Naira as against 129,104 Naira for those located in lowlands. It is therefore consistent with the results in Table 4 which show that living in an elevated area has significant effect on accessing communal safety nets and relocation. However, while the effect on communal safety nets is positive, the effect on relocation is negative. Thus, household heads whose houses are located in elevated areas have a higher probability of accessing communal safety nets and a lower probability of relocating to other areas. Expectedly, households located in high elevated areas may not be willing to relocate because they probably feel the area is already secured against floods. Relatedly, location in a flood hazard area (LFHA) had a significant positive effect on the decision to distil and access credit from banks as flood coping strategies. This implies that household heads who perceive that they are located in flood hazard areas have higher probabilities of engaging in distilling and accessing credit from banks. This justified the need to enhance the understanding of households on the nature of geographical locations in order to improve their decision-making.

Local emergency response groups (LERG) had a negative significant effect on the decision to relocate and access communal safety nets. Thus, household heads who have local emergency groups in their communities have a lower probability of accessing communal safety nets and relocating. This is consistent with the expectations since flood response decisions would be high in LERG than at the individual household levels. Because the local government response teams are mostly far from the communities or households, the LERG become the first call in flood disasters.

As expected, awareness of flood related programs (AFRP) had a significant positive effect on the decisions to seek assistance from the government and access credit from banks. This implies that household heads who are aware of flood related programs in their local government areas have a higher probability of adopting these flood coping strategies. These flood related programmes usually expose households to the various interventions available to flood victims and option of accessing credit from financial institutions. Thus, these programmes enhance the households' understanding and expose them to options to enhance their coping to floods.

Presence of early flood warning systems in community (PEFWSC) had positive effects on the adoption of all flood coping strategies except communal safety nets and access to credit from banks. However, the effect is significant for only accessing credit from banks. This result implies that household heads that are located in communities where there is PEFWSC have a lower probability of seeking credit from banks as a coping strategy. This is plausible since the presence of these early warning systems means that the households would be aware of the floods before they occur. In this case, the households can take some precautionary and temporal measures to avert the impacts.

Origin had a positive effect on the decision to relocate as a flood coping strategy. Thus, household heads who were in their home local government areas had a higher probability of relocating to other areas to cope with floods. This is contrary to the researcher's expectations that these households would be determined to stay in their home local government areas irrespective of climate shocks. However, these households may want to explore other options to stay safe from floods by relocating to other LGAs.

Relative to households in Ringim (the reference group), the local government area variables also had significant effects on various flood coping strategies. For instance, households located in Guri local government area were less likely to seek assistance from the government, distil, access communal safety nets, and relocate, relative to the households in Ringim local government area. Also, while households located in Hadeja local government area had lower probabilities of relocating, accessing assistance from friends, and distilling, these households also had higher probabilities of accessing assistance from the government, relative to those in Ringim. Locating in Kafin Hausa local government area had significant effects on all coping strategies. However, while the effects on assistance from government and accessing credit from banks are positive, those of communal safety nets, distilling, and assistance from friends are negative. The data shows that the average age, education, proportion of females and non-agricultural income of households in Ringim were above those in Guri and Kafin Hausa. These socioeconomic characteristics may tend to be the driving factors for the differences in the choice of flood coping strategies since there are little difference in the environmental conditions of the local government areas.

Table 5 shows the probability distribution for adopting all flood coping strategies and non-adoption. This indicate that the probability for a household to adopt all considered flood coping strategies is 0.0017 and this is less than the probability of households not adopting any of the coping strategies (0.042). This is consistent with the signs in the correlation matrix where most correlations were negative, indicating that most of the coping strategies are substitutes.

4.3. Random forest model predictions of flood coping strategies

This study applied the Random Forest Model estimation to give a further pictorial description of the relationship among flood coping strategies and to detail the extent to which the predictors influence the choice of the flood coping strategies. This involved the re-training of the data using the random forest model based on the out-of-bag error. Fig. 4 detail the out-of-bag error estimation result. The partial dependence plot was used for targets (variables to be predicted, which are captured as the flood coping strategies) that have classification rates of at least 85% using the two most predominate features: the two highest ranked predictors or socioeconomic variables based on the importance ranking

Table 5
Probability of adoption flood coping strategies.

Probability	Mean	Std. Dev.	Min	Max
Pr (Adopting all the Strategies)	0.0017	0.006	9.04E-13	0.059
Pr(Not adopting any of the strategies)	0.0424	0.049	6.22E-06	0.263

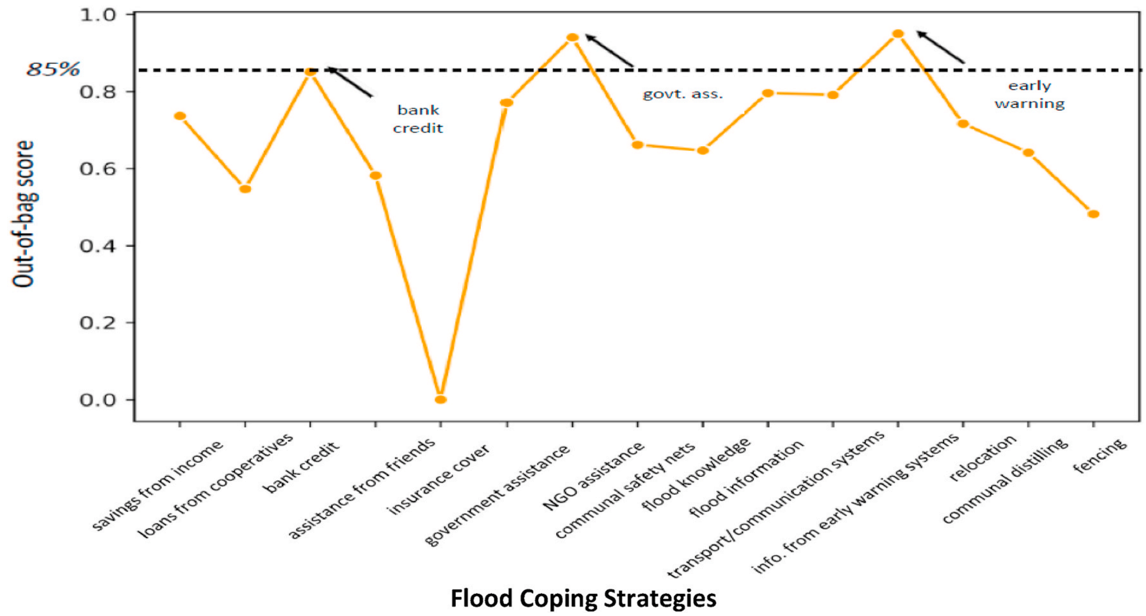

Fig. 4. Out-of-bag error plot.

plots.

From the out-of-bag error estimation, only three household flood coping strategies have scores of at least 85%. These coping strategies include access to credit from banks, assistance from the government and access to information from early warning systems. Thus, the importance ranking of the socioeconomic characteristics (predictors) was done for each of the three coping strategies to identify the two most influential household socioeconomic characteristics in terms of their ability to influence the adoption of these coping strategies. The results are presented as follows.

(a) Importance ranking and partial dependence plot for bank credit

Fig. 5 shows the importance ranking plot for bank credit as a flood coping strategy. This reveals that the two most influential socioeconomic variables explaining the use of credit from bank as a flood coping strategy are occupation and non-agricultural income. This is so because occupation has the highest weight followed by non-agricultural income. Hence, these two variables are used to plot the partial dependence plot (PDP) in Fig. 6. It indicates that although occupation influences the choice of bank credit as a coping strategy, only public sector and private sector employees have the highest probability to access credit from

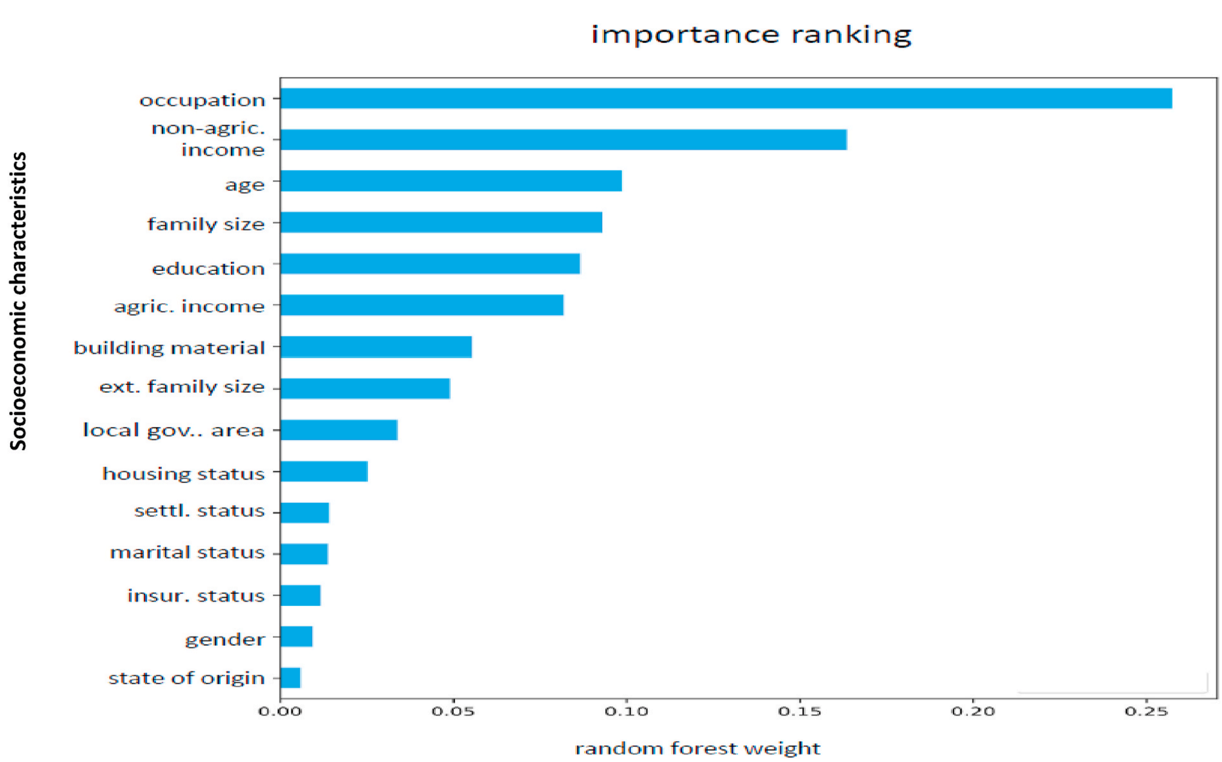

Fig. 5. Importance ranking plot for bank credit.

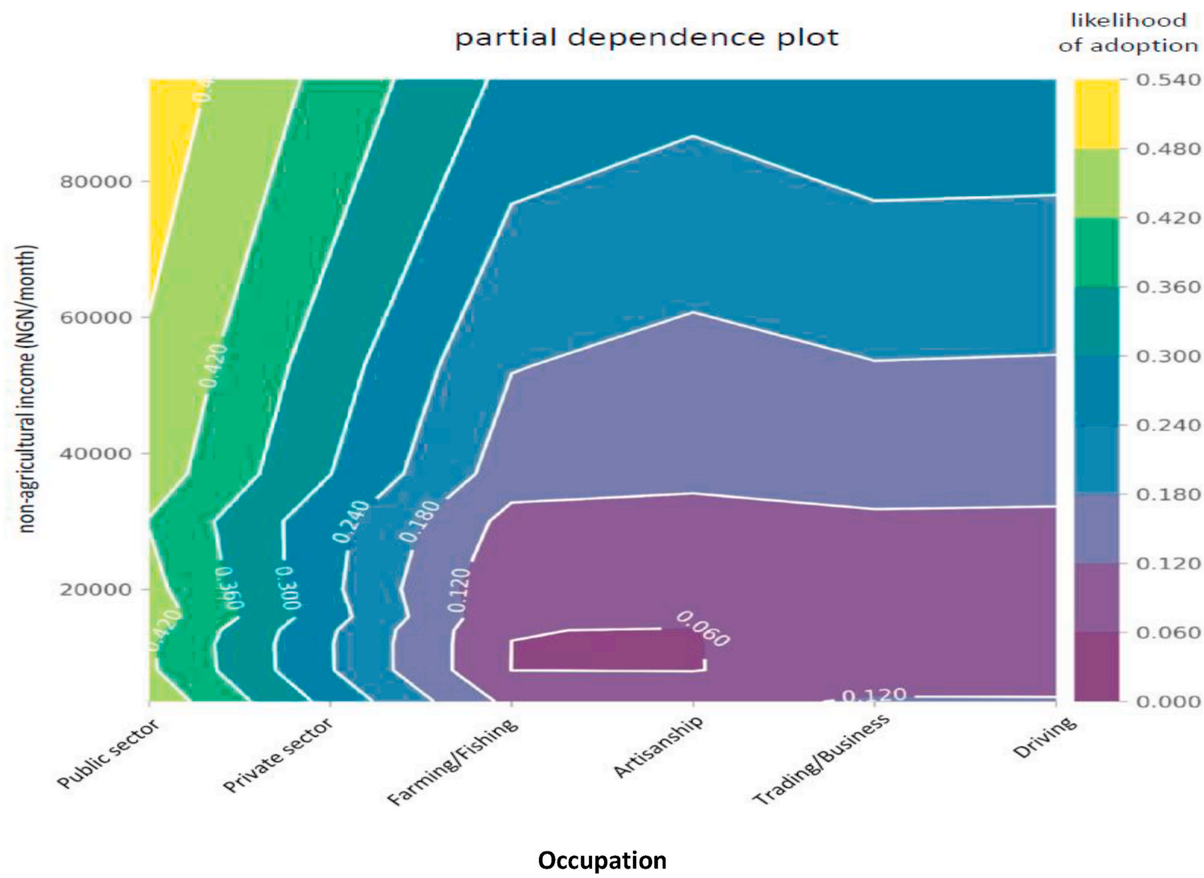

Fig. 6. Partial dependence plot for bank credit.

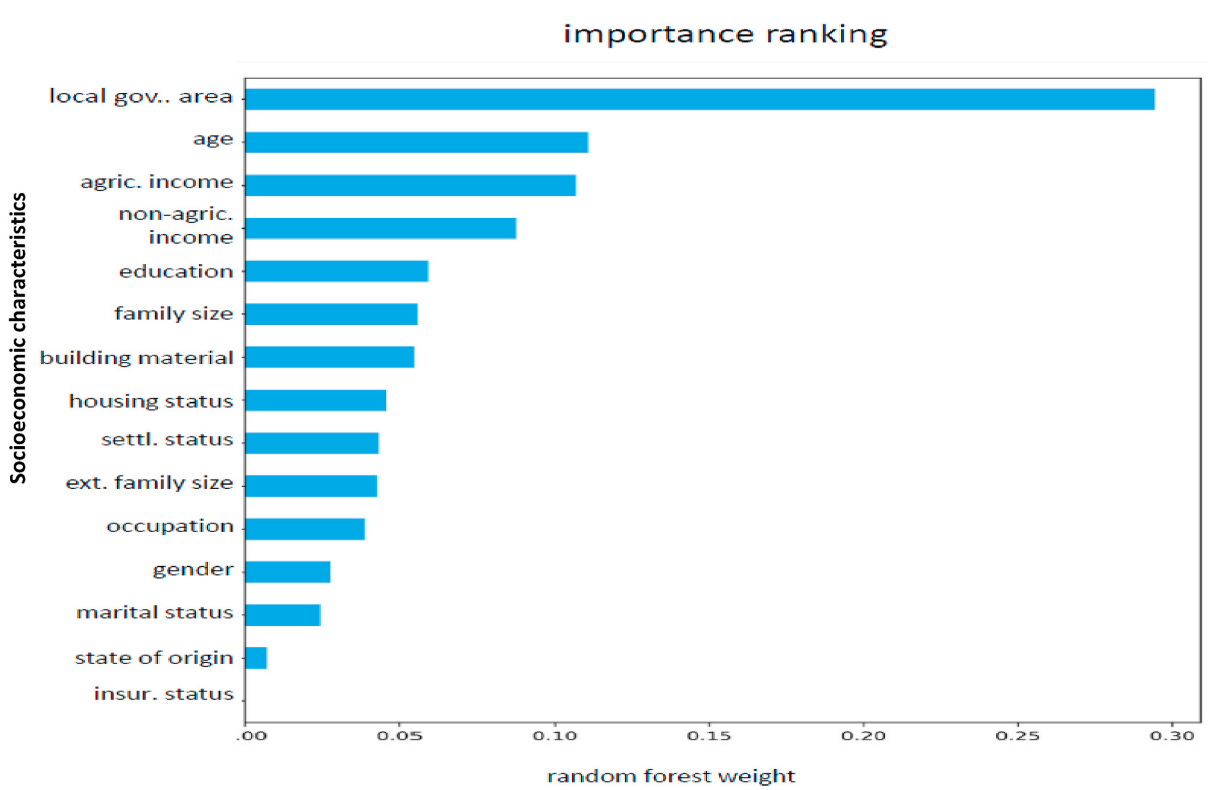

Fig. 7. Importance ranking plot for government assistance.

banks, and this is particularly associated with household heads with monthly non-agricultural income of at least 40,000 (about $110). Because these formal public and private sector workers have a defined income source that credit deductions can be made, the banks often prefer giving credit to these people. On the other hand, employees of other occupations such as farmers/fishermen, artisans, traders/businessmen and drivers may not be able to meet the collateral requirements for credits, hence their low probability of accessing credit from banks (Fig. 6).

(b) Importance ranking and partial dependence plot for assistance from government

From the importance ranking plot (Fig. 7), the two socioeconomic variables that are most influential in choosing assistance from government as a flood coping strategy are location (in terms of LGAs) and age. Recall that location variables in Table 4 had significant effects on seeking assistance from the government to cope with floods. These two variables are further examined in Fig. 8. This shows that younger household heads (those between the ages of 20 and 32 years), most of whom reside in Hadejia and Kafin Hausa LGAs have greater access to assistance from the government as a flood coping strategy than the elderly. Seeking assistance from government is less pronounced among household heads between the ages of 35 and 50, most of whom are located in Ringim and Guri LGAs. This is not surprising because those living in Hadejia and Kafin Hausa LGAs are closer to the government administrative areas, hence attracts the attention of the local authorities faster. In addition, the younger households are more likely to feel the impacts of flood hazards since they do not have as much assets to cushion them from flood impacts.

(c) Importance ranking and partial dependence plot for early warning information

The importance ranking plot (Fig. 9) shows that the two most influential socioeconomic variables associated with the choice of access to early warning information systems as a coping strategy are age and agricultural income. Agricultural income is ranked the highest and followed by age. The partial dependence plots (Fig. 10) indicates that the elderly household heads (between the ages of 50 and 65 years), predominantly those with very high agricultural income are more likely to rely on warnings of impending floods from early warning systems. This is lowest for the younger household heads with lower agricultural income. Generally, older people are risk averse, therefore, they would want to be aware of possible floods before taking any decision. On the other hand, the younger persons are risk takers, and would therefore not rely so much on such early warning information. Because of their leadership positions in the communities and households, the elderly household heads will be considering the impact of floods on the entire community, therefore, would want to rely on a a broader strategy like reliance on early warning systems. It is also expected that the younger household heads may be able to search for flood information and hence not depend as much on such early warning information systems.

5. Conclusion and recommendations

This paper examined the factors that determine households' choice of flood coping strategies to mitigate the effects of floods in Jigawa State, Nigeria. The study relied on survey data from 251 randomly selected households (flood victims of 2016). The study used a combination of Multivariate Probit Model (MVP) and Random Forest Model (RFM) for the estimations. Results from the MVP showed that a number of factors such as sex, age, education, occupation, income, housing status, flood warning systems, flood education significantly explained the decision of household heads to choose a particular flood coping strategy in the selected communities. It is also concluded from the RFM that access to credit from banks, seeking early warning information systems and assistance from government are crucial for coping with floods in the Jigawa State. The mixed effect of the variables on selecting a particular coping strategy means that policies and programmes designed to manage and reduce flood risks must take into account the inputs of all relevant stakeholders, particularly those of the poor and most

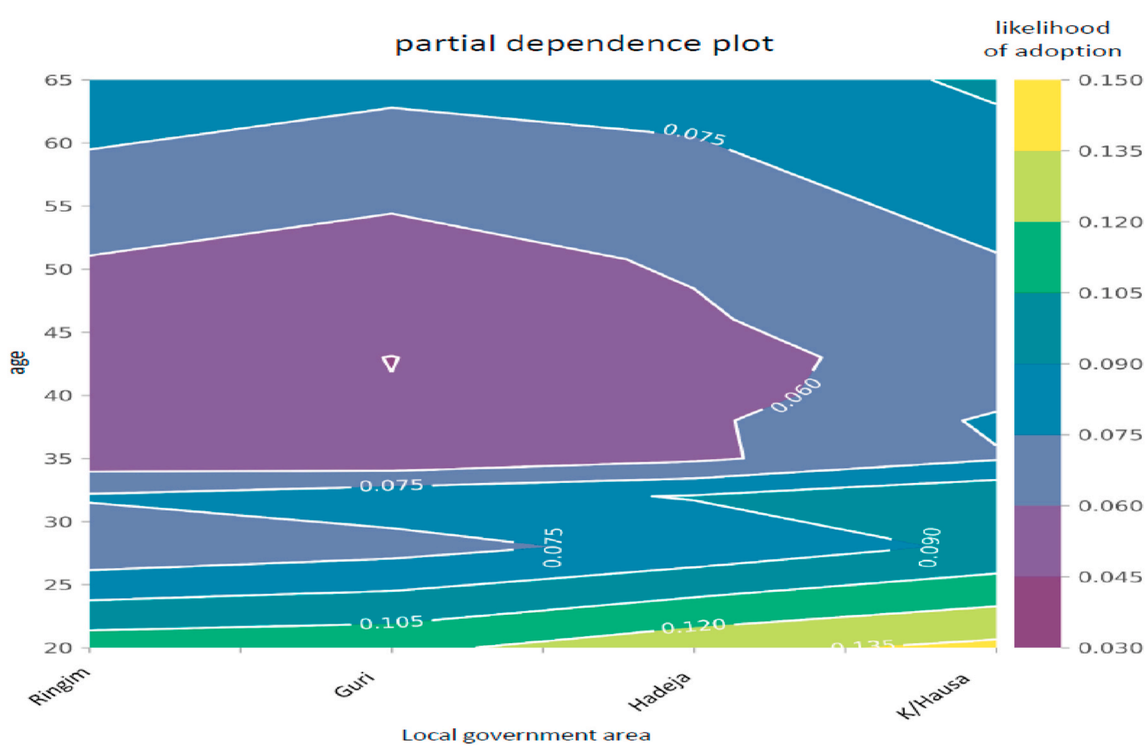

Fig. 8. Partial dependence plot for government assistance.

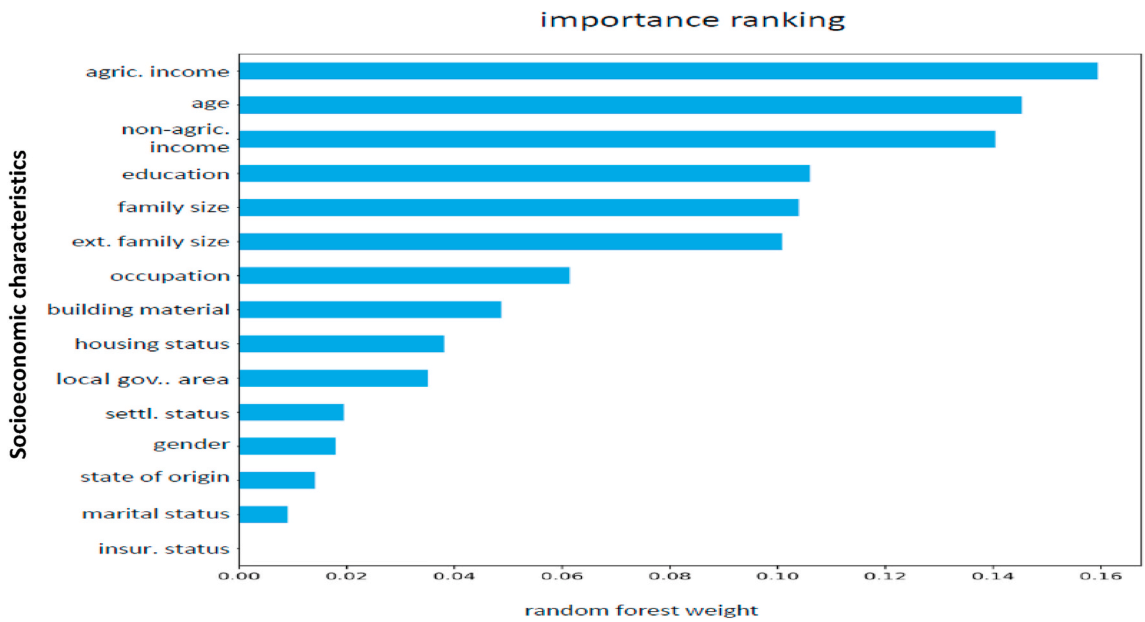

Fig. 9. Importance ranking plot for early warning information.

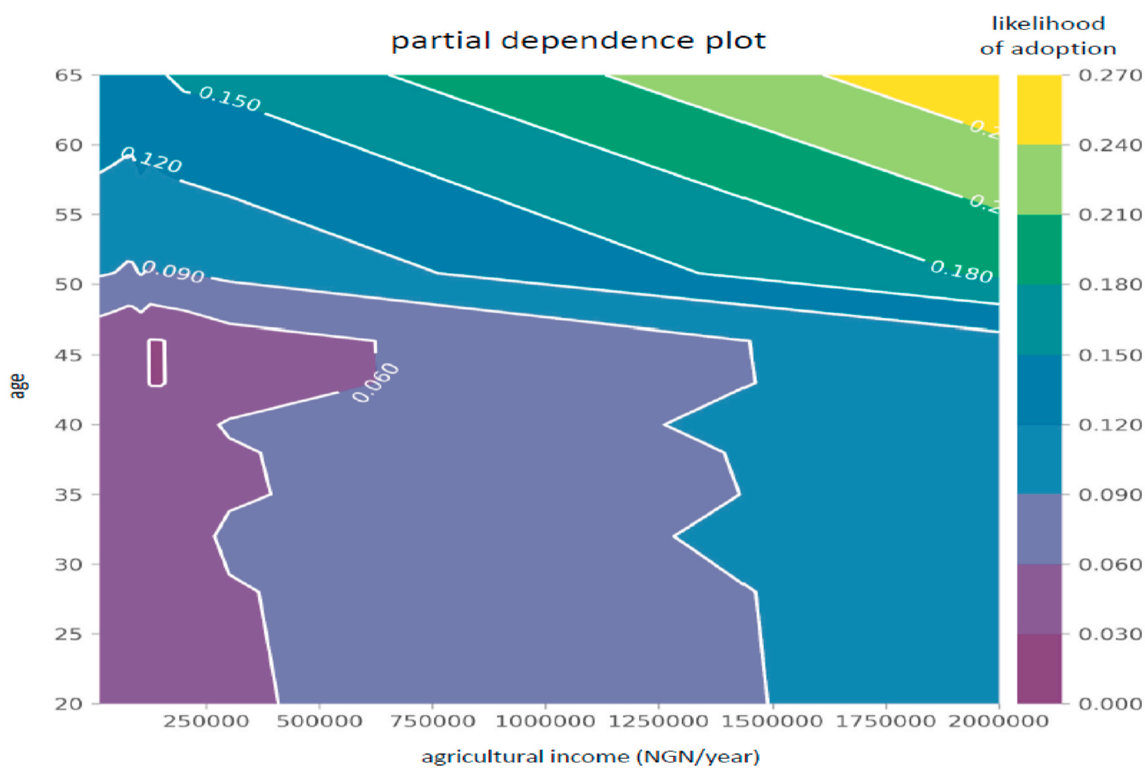

Fig. 10. Partial dependence plot for early warning information.

vulnerable groups. Most importantly, age and income differences and their implications have to be given keen attention to enhance coping with floods. The study also recommends the need for institutions in charge of flood disaster risk reduction and management to focus more on investing in non-structural measures of flood control such as providing early warning information in order to improve households resilience to floods. However, this should not undermine the need to keep investing in structural measures of flood control.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] K. Alam, M. Herson, I. Donnel, Flood Disasters: Learning from Previous Relief and Recovery Operations. Prevention Consortium and ALNAP, vol. 3, 2008. https://www.preventionweb.net/publications/view/2650.

[2] Intergovernmental Panel on Climate Change (IPCC), *Climate Change 2007*: Synthesis Report. Contribution of Working Groups I, II, and III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, Intergovernmental Panel on Climate Change, Geneva, 2007.
[3] World Bank, Cities and Climate Change: an Urgent Agenda, World Bank, Washington DC, 2011.
[4] R.K. Pachauri, M.R. Allen, V.R. Barros, J. Broome, W. Cramer, R. Christ, N. K. Dubash, Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change, Ipcc, 2014, p. 151.
[5] P. Kolsky, Storm Drainage: an Engineering Guide to the Low-Cost Evaluation of System Performance, IT Publications, London, UK, 1998.
[6] M. Muller, Adapting to climate change water management for urban resilience, Environ. Urbanization 19 (1) (2007) 99–113.
[7] F. Olorunfemi, Managing flood disasters under a changing climate: lessons from Nigeria and South Africa, Niser.Gov.Ng 1 (2011) 1–44. Retrieved from, http://niser.gov.ng/downloads/OLORUNFEMI NRSS DISCUSSION PAPER I.pdf.
[8] UNEP, Displacement and Environment in Africa: what Is the Relationship?, 2016. https://www.unenvironment.org/news-and-stories/story/displacement-and-environment-africa-what-relationship.
[9] K.A. Aderogba, Qualitative studies of recent floods and sustainable growth and development of cities and towns in Nigeria, Int. J. Acad. Res. Econ. Manag. Sci. 1 (3) (2012).
[10] A. Adeagbo, A. Daramola, A. Carim-Sanni, C. Akujobi, C. Ukpong, Effects of natural disasters on social and economic well being: a study in Nigeria, International Journal of Disaster Risk Reduction 17 (2016) 1–12, https://doi.org/10.1016/j.ijdrr.2016.03.006.
[11] A.Y. Daramola, O.T. Oni, O. Ogundele, A. Adesanya, Adaptive capacity and coping response strategies to natural disasters: a study in Nigeria, International Journal of Disaster Risk Reduction 15 (2016) 132–147, https://doi.org/10.1016/j.ijdrr.2016.01.007.
[12] A.S. Barau, R. Maconachie, A.N.M. Ludin, A. Abdulhamid, Urban morphology dynamics and environmental change in Kano, Nigeria, Land Use Pol. 42 (2015) 307–317, https://doi.org/10.1016/j.landusepol.2014.08.007.
[13] D. Guha-Sapir, Ph Hoyois, R. Below, Annual Disaster Statistical Review 2012: the Numbers and Trends, CRED, Brussels, 2013. http://www.cred.be/sites/default/files/ADSR_2013.pdf.
[14] Emdat, Report on Flooding, 2015. https://www.emdat.be/.
[15] S.M. Tapsell, E.C. Penning-Rowsell, S.M. Tunstall, T.L. Wilson, Vulnerability to flooding: health and social dimensions, Phil. Trans. Roy. Soc. Lond.: Mathematical, Physical and Engineering Sciences 360 (1796) (2002) 1511–1525.
[16] P.R. Hunter, Climate change and waterborne and vector-borne disease, J. Appl. Microbiol. 94 (s1) (2003) 37–46.
[17] S.M. Tapsell, S.M. Tunstall, "I wish I'd never heard of Banbury": the relationship between 'place 'and the health impacts from flooding, Health Place 14 (2) (2008) 133–154.
[18] M.C. Obeta, Institutional approach to flood disaster management in Nigeria: need for a preparedness plan, Br. J. Appl. Sci. Technol. 4 (33) (2014) 4575.
[19] NEMA-National Emergency Management Agency, Report on Flood Disasters in Nigeria, Government Press, Abuja, 2013.
[20] G. Fadairo, S.A. Ganiyu, July). Effects of flooding on the built environment in Akure, Nigeria, in: WEST AFRICA BUILT ENVIRONMENT RESEARCH (WABER) CONFERENCE, 2010, p. 281.
[21] E.F. Ogunbodede, R.A. Sunmola, Flooding and traffic management in Akure (Nigeria) metropolitan environment, European Environmental Sciences and Ecology Journal (EES) 24 (2014).
[22] Action Aid, Climate Change, Urban Flooding and the Rights of the Urban Poor in Africa: Key Findings from Six African Cities, Action Aid International, London, 2006. https://www.actionaid.org.uk/sites/default/files/doc_lib/urban_flooding_africa_report.pdf.
[23] A.J. Adeloye, R. Rustum, Lagos (Nigeria) flooding and influence of urban planning, Proceedings of the Institution of Civil Engineers-Urban Design and Planning 164 (3) (2011) 175–187.
[24] I. Douglas, K. Alam, M. Maghenda, Y. Mcdonnell, L. McLean, J. Campbell, Unjust waters: climate change, flooding and the urban poor in Africa, Environ. Urbanization 20 (1) (2008) 187–205.
[25] O.O. Bashir, A.H. Oludare, O.O. Johnson, B. Aloysius, Floods of fury in Nigerian cities, J. Sustain. Dev. 5 (7) (2012) 69.
[26] N.P. Iloje, A New Geography of Nigeria, Lagos. Longman International Education Division (a Pearson Education company, 2004.
[27] U. Nkwunonwo, W. Malcolm, B. Brian, Flooding and flood risk reduction in Nigeria: cardinal gaps, J. Geogr. Nat. Disasters 5 (2015) 136.
[28] F.H. Norris, S.P. Stevens, B. Pfefferbaum, K.F. Wyche, R.L. Pfefferbaum, Community resilience as a metaphor, theory, set of capacities, and strategy for disaster readiness, Am. J. Community Psychol. 41 (1–2) (2008) 127–150.
[29] M.B.B.L. Villordon, P. Gourbesville, Community-based flood vulnerability index for urban flooding: understanding social vulnerabilities and risks, in: Advances in Hydroinformatics, Springer, Singapore, 2016, pp. 75–96.
[30] S.F. Balica, N.G. Wright, F. van der Meulen, A flood vulnerability index for coastal cities and its use in assessing climate change impacts, Nat. Hazards 64 (1) (2012) 73–105.
[31] S.L. Cutter, C.G. Burton, C.T. Emrich, Disaster resilience indicators for benchmarking baseline conditions, J. Homel. Secur. Emerg. Manag. 7 (1) (2010).
[32] M. Moench, A. Dixit, Adaptive Capacity and Livelihood Resilience: Adaptive Strategies for Responding to Floods and Droughts in South Asia, Institute for Social and Environmental Transition (ISET), 2004.
[33] J. Rawadee, M. Areeya, Adaptive Capacity of Households and Institutions in Dealing with Floods in Chiang Mai, Thailand, EEPSEA, IDRC Regional Office for Southeast and East Asia, Singapore, SG, 2011.
[34] S.L. Cutter, B.J. Boruff, W.L. Shirley, Social vulnerability to environmental hazards, Soc. Sci. Q. 84 (2) (2003) 242–261.
[35] National Population Commission-NPC, Population and Housing Census of the Federal Republic of Nigeria. Priority Tables, 1, 2016.
[36] K. Ahmed, The Kano physical environment, in: A.U. Adamu, I. Ado-Kurawa (Eds.), Perspectives on Kano, vol. 1, Inuwar Jama'ar Kano (Kano Forum) Telletes Press, Lagos, 2010, pp. 7–46.
[37] Nigerian Meteorological Agency–NIMET, Nigeria Climate Review Bulletin 2007, Nimet-No. 001, February 2008, Abuja, 2008.
[38] NEMA-National Emergency Management Agency, Database on Flood Disasters in Nigeria, 2016.
[39] S. Rahman, S. Akter, Determinants of livelihood choices: an empirical analysis from rural Bangladesh, J. S. Asian Dev. 9 (3) (2014) 287–308.
[40] W.H. Greene, Econometric analysis, 71e, Stern School of Business, New York University, 2012.
[41] L. Breiman, Random forests, Mach. Learn. 45 (1) (2001) 5–32.
[42] T. Hastie, R. Tibshirani, J. Friedman, The Elements of Statistical Learning: Data Mining, Inference, and Prediction, Springer Series in Statistics, 2009. https://web.stanford.edu/~hastie/Papers/ESLII.pdf.
[43] N. Wang, G. Shi, X. Zhou, To move or not to move: how farmers now living in flood storage areas of China decide whether to move out or to stay put, Journal of Flood Risk Management 13 (2020) 1–12, https://doi.org/10.1111/jfr3.12609, e312609.
[44] T.M. Nji, R.A. Balgah, Determinants of coping strategies to floods and droughts in multiple geo-ecological zones, in: Natural Hazards - Risk, Exposure, Response, and Resilience, 2019, https://doi.org/10.5772/interchopen.84571.
[45] W. Cao, Y. Yang, J. Huang, D. Sun, G. Liu, Influential factors affecting protective coping behaviors of flood disaster: a case study in Shenzhen, China, International Journal of Environmental Health and Public Research 17 (2020) 5945, https://doi.org/10.3390/ijerph17165945.