

A Cross-Sectional Survey of Households in Nigeria on Prevalence of Food Insecurity Using Bayesian Logistic Regression Analysis

Rotimi Kayode Ogundeji^{1*}, Ayoade Iyabode Adewole², and Stephen Bernard Ahem¹

¹Department of Statistics, Faculty of Science, University of Lagos, Akoka, Nigeria

²Department of Mathematics, Tai Solarin University of Education, Ijagun, Ogun State, Nigeria

*Corresponding Author: rogundeji@unilag.edu.ng

ABSTRACT

Food insecurity remains an important concern in Nigeria. It is a situation where lack of funds and other resources occasionally limits access to enough food throughout the year. Despite numerous attempts to restore food security, policymakers and other decision-makers must give this pressing social issue their full attention. The study looks to identify key factors influencing food insecurity at the household level in Yewa-North Local Government Area in Ogun State, Nigeria. Food insecurity incidence was assessed using questions adapted from the U.S. household food security survey module, and it was found to be 60.3%. Bayesian modeling was utilized to also determine important drivers of food insecurity. The study used a cross-sectional survey of 350 households chosen through systematic random sampling, employing a structured questionnaire for data collection. Various household categories based on their degree of food insecurity (high, marginal, low, and very low food security) were investigated. Additionally, strategies for interventions to lower food insecurity in households are provided, along with recommendations on how to mitigate the significant predictors of food insecurity that are identified.

Keywords: cross-sectional, food insecurity, logistic model, posterior distribution, households survey

INTRODUCTION

Food security (FS) is the condition in which people have access to sufficient food to live healthy and productive lives (Peng & Berry, 2019). Odey et al. (2022) defined FS as a situation “When all people at all times have physical, social and economic access to sufficient food to meet their dietary needs for a

productive and healthy life” (p. 36). The major fundamentals of FS outlined the availability, accessibility, utilization, and stability of food at any level including individuals, households, or regions (Ayinde et al., 2020; Ojo & Adebayo, 2012; Piperata et al., 2023). Furthermore, FS relies on agricultural production, food imports and grants, employment opportunities and income revenues, intrahousehold decision-

making and allocation of assets, health care utilization, and caring practices. According to the United Nations, FS is described as the ability of people to have physical, economic, and social access at all times to sufficient food that is safe and nutritious which simultaneously satisfies their dietary needs and food preferences for a healthy lifestyle (Food and Agriculture Organization [FAO] & World Food Summit, 1996). Even though there has been a long-term decrease in the number of hungry people, FAO et al. (2019) found that it has been gradually rising since 2015.

Food insecurity (FI) is a situation in which access to sufficient food is limited at times during the year because of lack of money and other resources. FI arises when there is a scarcity of safe, nutritious food or when there is an absence of knowledge about how to get food in ways which are acceptable to humanity (FAO et al., 2019). Generally, researchers such as Okoro (2018), McKay et al. (2019), Salik and Aras (2020), and George et al. (2021) among others have established that people were exposed to FI through certain conditions such as inflation, corruption, ill health, unstable food access, unemployment, terrorism, and nonexistent social protection programs. In line with Ajetunmobi (2024), FS requires adequate attention because of notable effects of FI on individuals, households, and communities, intensifying susceptibilities, disrupting social consistency and financial equilibrium. Various researchers have described the holistic approaches that address the underlying issues and the effects of FI on Nigerian economy and analyze ways of promoting sustainable solutions for healthier Nigerians (Balana et al., 2023; Bofa & Zewotir, 2024; Kasuwa, 2024; Ogundare, 2015; Ogunniyi et al., 2021; Ogwumike et al., 2019; Olayiwola et al., 2017) among others. Over time, scholars have demonstrated the feasibility of numerous Bayesian models in enhancing the effectiveness of studying and analyzing FI both in Nigeria

and globally. Efrem (2020) employed Bayesian multiple linear regression analysis to examine the determinants of FI and diet quality among rural households in Ethiopia using data obtained from the Household Consumption and Expenditure (HCE) Survey and Welfare Monitoring Survey (WMS) conducted in 2011 by the Central Statistical Agency (CSA). According to their study, 32% of rural households were food insecure and 68% of them were food secure. The analysis's findings demonstrated that the most significant factors influencing a household's FI were its head of household's educational attainment, annual per capita income, farm land size, number of oxen owned, head of household's age, household size and gender, and participation in off-farm activities, as well as production storage and shocks like food item prices, floods, droughts, and illnesses. Akbar et al. (2021) used the Bayesian logit model to assess the impact of several significant socioeconomic factors, such as parental job availability and schooling, on the FS of households in Pakistan employing 14,948 households' cross-sectional data taken from national surveys. According to the study's findings, Pakistan's FS situation can be improved by maternal and paternal paid employment as well as other parental employment.

This study evaluates the incidence and important indicators of FI at the household level in Yewa-North Local Government Area, Ogun State, Nigeria, using both descriptive statistics and a Bayesian logistic regression model. The frequency of FI was evaluated using descriptive statistics, and the key factors influencing FI at the household level were found using Bayesian logistic regression analysis. This research endeavors to present iterative methods in the application of Bayesian regression procedures on FI in Nigeria with a logistic model.

MATERIALS AND METHODS

Study Area, Data Collection, and Variables

This study is carried out in Yewa-North Local Government Area in western Ogun State, Nigeria, which borders the Republic of Benin. Its total area is 2,087 km² having its headquarters located in Ayetoro Town. Among the 20 local governments in Ogun State, it has the largest expanse of land with a size of 200,213.5 hectares, and it had a population of 183,844 during the 2006 Census while the population projection as of March 21, 2022 is 312,700.

A household-based cross-sectional investigation in which the surveyed group consisted of all households in the subject region at the survey time was carried out in Yewa-North to explore the level of FI and its contributing factors. Structured survey responses are used for collection of main or important information from specified people for this study. The intention of the survey was to collect qualitative as well as quantitative data covering a range of topics including socioeconomic and demographic variables. The explanatory variables taken from various related literature are factors that influence FI of households, such as age, marital status, religion, gender, and educational attainment of the household head; family size; and land size. Furthermore, some of the factors contributing to household FI such as the agroecological zone, saving practices, agricultural drilling, watering activities, slope of agricultural land, funding status, making use of enhanced seeds, application of compost, title to land, soil fertility of agricultural land, and tropical animal products were inclusive.

METHODS

The methodology outlines the steps involved in Bayesian inference centering on the

logistic regression model's prior distribution, likelihood function, and posterior distribution.

Bayesian Logistic Regression Model

Statistical inferences are based on maximum likelihood estimation (MLE). MLE presumes that parameters are estimated with a certain degree of confidence and are assumed to be fixed but unknown. In Bayesian analysis, the unknown parameters are treated as random variables and the degree of uncertainty about them is measured using probability. Bayesian inference is the process of evaluating statistical models while previous information about the model is known. The inferences spring from Bayes's theorem originated by Thomas Bayes. Posterior distribution is simplified as follows:

$$\begin{aligned}
 &P(\text{Parameters}|\text{data}) \\
 &= \frac{P(\text{data}|\text{Parameters}) \times P(\text{Parameters})}{P(\text{data})} \\
 &\propto \text{Likelihood} \times \text{Prior} \tag{1}
 \end{aligned}$$

where $P(\text{Parameters}|\text{data})$ is called the posterior probability to calculate the probability of the parameters given the data; $P(\text{data}|\text{Parameters})$ is the probability of the data given the parameters, called the likelihood function; and $P(\text{Parameters})$ and $P(\text{data})$ are the prior probability of the parameters and data, respectively.

For data with a dichotomous response variable, logistic regression is suitable. The logistic regression model employing Bayesian process based on the average response can be expressed as

$$E(Y_i|x) = \frac{e^{\beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \beta_3 X_{i3} + \beta_0 X_{ip}}}{1 + e^{\beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \beta_3 X_{i3} + \beta_0 X_{ip}}} \tag{2}$$

The response variable Y assumes the value 0 or 1 while its expected value is equivalent to $P(Y=1)$, relating to a set of predictor x s. The applied

logistic regression model is a multivariate Bayesian logistic regression model based on multiple variables and coefficients included in the model (Erp & Gelder, 2013).

Likelihood Function

A binomial distribution is the sum of independent and identically distributed Bernoulli trials, and the joint distribution of “n” independent Bernoulli trials is the product of each Bernoulli distribution.

Let \dots , be defined as independent Bernoulli trials with \dots , as the probability of success, respectively; the joint distribution of \dots , is the combination of independent Bernoulli probabilities. That is,

$$\begin{aligned} L(\text{data}|\beta) &= \prod_{i=1}^n P(Z_i|X_{i1}, X_{i2}, \dots, X_{ip}) \\ &= \prod_{i=1}^n P_i^z [1 - P_i]^{1-z} \end{aligned} \quad (3)$$

Prior Distribution

Prior distribution makes explicit the prior knowledge about an uncertain parameter before observing any data in statistical analysis. The prior estimate for the parameter is given by prior mean, whereas its variance clarifies the degree of uncertainty encompassing this estimate. There is different usage of forms of prior; informative priors are employed when there is some knowledge regarding the unknown parameters values. Vague priors or noninformative priors are employed when there is no prior knowledge. For logistic regression parameters, the most popular priors are typically those with a large variance and a mean of 0.

Logistic regression parameter mostly makes use of normal prior with mean and variance, and the distribution of prior is denoted by

$$f(\beta_j) = \frac{1}{\sigma_j \sqrt{2\pi}} \exp \left[-\frac{1}{2} \left[\frac{\beta_j - \mu_k}{\sigma_k} \right]^2 \right] \quad (4)$$

Normal distributions are conjugate priors for logistic regression’s likelihood function, which simplifies the computation of the posterior distribution.

The Posterior Distribution

The posterior distribution is the combination of prior and likelihood function, expressed below as

$$\begin{aligned} f(\beta|\text{data}) &\propto \prod_{i=1}^n P_i^Y [1 - P_i]^{1-Y} \times \\ &\frac{1}{\sigma_j \sqrt{2\pi}} \exp \left[-\frac{1}{2} \left[\frac{\beta_j - \mu_j}{\sigma_j} \right]^2 \right] \end{aligned} \quad (5)$$

where $f(|\text{data})$ is the posterior function simplified as combination of likelihood function and the normal prior functions.

A point estimate of β can be obtained from the mean of the posterior distribution, but it may be challenging to get an analytical estimate of β from the posterior distribution. Thus, nonanalytical approaches such as simulation techniques are employed. The most widely used of these approaches is the Markov Chain Monte Carlo (MCMC) method. As a result, the mean of the sampled Markov chain values following the burn-in period can be used to determine the posterior mean of the parameters.

Bayesian Logistic Regression Model Evaluation

MCMC Methods. Direct draws from a complex distribution of interest are attempted to be simulated using MCMC methods. The Metropolis–Hastings and Gibbs sampler is the most popular MCMC method.

Convergence of the Algorithm. Convergence of the Monte Carlo chain is very essential before summarizing the simulated parameters. The most widely used and straightforward techniques for evaluating convergence are as follows: time series plots, density plots, autocorrelation, and the Gelman-Rubin statistic.

The Burn-In Period. The process of eliminating some iteration at the beginning of an MCMC run is known colloquially as “burn-in.”

Assessing Accuracy of the Bayesian Logistic Regression. Convergence evaluation can be implemented with the aid of plots and evaluation statistic. Also, the precision of MCMC can be assessed by minimal Monte Carlo error for each parameter usually less than 5%.

RESULTS AND DISCUSSION

In this study, households’ FI status was assessed using the 18-item core FS module question series created by the United States Department of Agriculture. The magnitude of FI for 350 homes in Yewa-North was taken into account. The Bayesian methods were utilized to obtain the model parameter estimates.

Results on Magnitude of FI Status of Households Based on Socio-demographic Characteristics

Table 1 includes the total sample, frequency, and percentage of homes that fall under food secure and food insecure. The respective relative frequency of each variable under the FI and FS classifications is presented in parentheses across various demographic categories.

Household FI Rate Status in Relation to Economic and Agricultural Environment Features

Table 2 shows the association between households’ economic, practice-related, and agricultural environment characteristics and their level of FS. The total sample, frequency, and percentage of FS and FI of the respective variables are presented. The respective relative frequency of each variable under the FI and FS classifications is presented in parentheses.

From Table 2, households were distributed across three agroecological zones, namely, Ayetoro Ward I, which includes 48.9% of the households and had 25.7% of households classified as food insecure and 23.1% as food secure; Ayetoro Ward II, comprising 32.6% of the sample and with 22.3% classified as food insecure and 10.3% as food secure; and Imasayi Ward, representing 18.6% of households with 12.3% classified as food insecure and 6.3% as food secure.

Bayesian Logistic Regression Analysis

Summary statistics of Bayesian logistic regression analysis obtained from the sampled values based on sociodemographic characteristics is given in Table 3. This includes the model coefficient β , model coefficient odd ratio (OR), and Markov chain error.

Table 1. The Prevalence of Sociodemographic Characteristics with Food Security Status of Household

Variables	Total Number	Total Percentage	Food Insecure Percentage (Relative Frequency)	Food Secure Percentage (Relative Frequency)
Food security status	350	100%		
Sex of the head of the household				
Female	112	32%	21.7% (0.68)	10.30% (0.32)
Male	238	68%	38.60% (0.57)	29.40% (0.43)
Age of the head of the household				
18–35	80	22.10%	14.0% (0.61)	8.9% (0.39)
36–44	84	24.00%	16.30% (0.68)	7.70% (0.32)
45–65	160	45.70%	25.70% (0.56)	20.00% (0.44)
Greater than or equal to 65	26	7.40%	4.30% (0.58)	3.10% (0.42)
Religion of the head of the household				
Christianity	155	44.3%	24.0% (0.54)	20.30% (0.46)
Muslim	126	36.00%	23.4% (0.65)	12.60% (0.35)
Traditional	69	19.71%	12.9% (0.65)	6.81% (0.35)
Educational status of the head of the household				
Illiterate	130	37.10%	23.4% (0.63)	13.70% (0.37)
Literate	220	62.90%	36.9% (0.59)	26.00% (0.41)
Marital status of the head of the household				
Single	98	28.00%	16.60% (0.59)	11.40% (0.41)
Married	224	64.00%	38.90% (0.61)	25.10% (0.39)
Divorce	28	8.00%	4.90% (0.61)	3.10% (0.39)
Family size of the household				
Less than 4	142	40.6%	24.9% (0.62)	15.70% (0.38)
Exactly 6	188	51.7%	33.1% (0.62)	20.60% (0.38)
Greater than or equal to 7	20	5.7%	2.3% (0.40)	3.40% (0.60)

Table 2. The Distribution of Food Security Status of Households with Agricultural Environmental and Economic Features

Variables	Total Number	Total Percentage	Food Insecure Percentage (Relative Frequency)	Food Secure Percentage (Relative Frequency)
Food security status	350	100%		
Agroecological zone				
Ayetoro Ward I	171	48.9%	25.7% (0.53)	23.10% (0.47)
Ayetoro Ward II	114	36.60%	22.30% (0.68)	10.3% (0.32)
Imasayi Ward	65	18.60%	12.30% (0.66)	6.30% (0.34)
Slope of the land				
Gentle slope	52	14.90%	10.9% (0.73)	4.00% (0.27)
Medium	160	45.7%	27.4% (0.60)	18.3% (0.40)
Level	138	39.4%	22.0% (0.56)	17.4% (0.44)
Saving habit				
No	181	51.7%	32.6% (0.62)	19.10% (0.38)
Yes	169	48.3%	27.7% (0.57)	20.6% (0.43)
Practicing irrigation				
No	60	17.10%	9.40% (0.55)	7.70% (0.45)
Yes	290	82.90%	50.90% (0.61)	32.0% (0.39)
Size of the land in hectares				
Less or equal to 1.5	103	29.40%	16.90% (0.57)	12.6% (0.43)
1.6 to 2	198	56.60%	36.30% (0.64)	20.3% (0.36)
Greater than 2	49	14.0%	7.10% (0.51)	6.90% (0.49)
Have they taken a loan?				
No	205	58.6%	33.70% (0.58)	24.9% (0.42)
Yes	145	41.4%	26.6% (0.64)	14.9% (0.36)
Size of the tropical levels				
Less or equal to 2.5 hectares	134	38.28%	24.9% (0.65)	13.38% (0.35)
Greater than or equal to 2.5 hectares	216	61.7%	35.4% (0.57)	26.3% (0.43)
Use of improved seed on the farm				
No	220	62.9%	36.3% (0.58)	26.60% (0.42)
Yes	130	37.10%	24.0% (0.65)	13.10% (0.35)
Attended any training by agricultural professional				
No	204	58.3%	34.0% (0.58)	24.3% (0.42)
Yes	146	41.70%	26.3% (0.63)	15.4% (0.37)
Soil fertility of the agricultural land				
Infertile	115	32.9%	21.7% (0.66)	11.1% (0.34)
Fertile	235	67.1%	38.6% (0.57)	28.5% (0.43)
Use of fertilizer				
No	52	14.90%	12.3% (0.83)	2.6% (0.17)
Yes	298	85.10%	50.0% (0.59)	35.10% (0.41)
Ownership nature of the land				
Rent/lease	80	22.99%	12.9% (0.56)	10.0% (0.44)
Private	270	77.10%	47.40% (0.62)	29.7% (0.38)

Table 3. Summary Statistics of the Posterior Distribution of the Model Parameters Obtained from the Sampled Values Based on Socio-demographic Characteristics

Variable	Categories	Model Coefficient	Model Coefficient Odds Ratio ()	Markov Chain Error
(Intercept)		-1.1		0.8
Sex of the head of the household	Female			
	Male	0.4	1.492	0.3
Age of the head of the household	18–35 years			
	36–44 years	-0.2	0.819	0.4
	45–65 years	0.2	1.221	0.3
	Greater than or equal to 65 years	0.2	1.221	0.5
Religion practiced by the head of the household	Christian			
	Muslim	-0.4	0.670	0.3
	Traditional	-0.5	0.607	0.4
Educational status of the head of the household	Literate	0.5	1.649	0.3
Marital status of the household head	Single			
	Married	-0.2	0.819	0.3
	Divorced	0.3	1.349	0.5
Family size of household	Less than 4			
	4–6	-0.1	0.905	0.3
	Greater than or equal to 7	1.1	3.000	0.6

The Bayesian logistic regression analysis examined the determinants of household FS; various household characteristics were evaluated to understand their impact on the likelihood of the household being food secure. The model's intercept is -1.1, corresponding to an odds ratio of approximately 0.33, which sets a low baseline probability for FS when all predictors are at their baseline.

The household head's sex stands as a major predictor, with male-headed households showing a positive coefficient of 0.4 and an odds ratio of 1.49. This indicates that male-headed households are about 49% more likely to be food secure than female-headed

households. The age of the household head shows varying impacts across different age groups. Compared to the reference group of 18–35 years, household heads aged 36–44 years have a negative coefficient of -0.2 (odds ratio = 0.82), suggesting that they tend to be less food secure. In contrast, those aged 45–65 years and greater than or equal to 65 years have positive coefficients of 0.2 (odds ratio = 1.22), indicating these older age groups are about 22% more likely to be food secure.

Religion also plays a crucial role. Muslim household heads have a negative coefficient of -0.4 (odds ratio = 0.67), and those practicing traditional religions have a coefficient of -0.5

(odds ratio = 0.61), making them less likely to be food secure compared to Christian households, with traditional religion practitioners being the least likely. Educational status significantly affects FS, with literate household heads having a positive coefficient of 0.5 and an odds ratio of 1.65. This implies that literate heads are about 65% more likely to be food secure than their illiterate counterparts. Marital status impacts FS differently. Married household heads have a negative coefficient of -0.2 (odds ratio = 0.82), making them less likely to be food secure compared to single heads. However, divorced heads have a positive coefficient of 0.3 (odds ratio = 1.35), indicating they are more probable to have nutritional security.

Family size has a complex relationship with FS. Households with four to six members have a slight negative coefficient of -0.1 (odds ratio = 0.90), suggesting a minor decrease in FS likelihood. However, households with seven or more members have a positive coefficient of 1.1 (odds ratio = 3.00), indicating they are three times more likely to have abundant food.

The output of Bayesian logistic regression analysis based on agricultural environment and economic and practice-related characteristics is presented in Table 4 below. This includes the model coefficient, model coefficient odd ratio, and Markov chain error. It shows that the agroecological zone where the households are located also affects food abundance.

Households in Ayetoro Ward II and Imasayi Ward have negative coefficients of -0.6 (odds ratio = 0.55), indicating these households are less probable to be food secure compared to those in Ayetoro Ward I.

The slope of the land on which the household is situated shows that households on medium and level slopes both have positive coefficients of 0.6 (odds ratios = 1.82), suggesting these slopes significantly increase the likelihood of FS compared to gentle slopes. Saving habits positively affect FS, with households that

save having a positive coefficient of 0.3 (odds ratio = 1.35), indicating a higher likelihood of being nutritionally safe. Practicing irrigation has a negative impact, with a coefficient of -0.3 (odds ratio = 0.74), suggesting households that practice irrigation are less probable to be food secure.

The size of the landholding in hectares is another critical factor. Households with 1.6 to 2 hectares show a slight negative coefficient of -0.1 (odds ratio = 0.90), whereas those with more than 2 hectares have a positive coefficient of 0.4 (odds ratio = 1.49), indicating larger landholdings improve FS. Taking a loan is associated with a negative coefficient of -0.4 (odds ratio = 0.67), suggesting that families with loans are more unlikely to be nutritionally safe. The size of tropical livestock shows a negative coefficient of -0.2 (odds ratio = 0.82), indicating that households with larger livestock sizes are less likely to be food secure.

The use of improved seeds has a positive coefficient of 0.4 (odds ratio = 1.49), suggesting that households using improved seeds are less probable to be nutritionally secure. Attending agricultural training negatively affects FS, with a coefficient of -0.6 (odds ratio = 0.55), indicating households that have attended training are unlikely to be food secure. Soil fertility has a positive impact, with fertile soil showing a coefficient of 0.3 (odds ratio = 1.35), suggesting that fertile soil increases the likelihood of FS. The use of fertilizer is positively associated with FS, with a coefficient of 0.5 (odds ratio = 1.65), indicating households using fertilizer are more likely to be food secure. Finally, ownership nature of land shows that households renting or leasing land have a negative coefficient of -0.2 (odds ratio = 0.82), indicating they are rare to be food secure compared to those owning private land.

Table 4. Posterior Distribution Statistics of the Model Parameters from Agricultural, Environmental, and Economical Features

Variable	Categories	Model Coefficient	Model Coefficient Odd Ratio ()	Markov Chain Error
Agroecological zone	Ayetoro Ward I			
	Ayetoro Ward II	-0.6	0.549	0.3
	Imasayi Ward	-0.6	0.549	0.4
Slope of the land	Gentle slope			
	Medium	0.6	1.822	0.4
	Level	0.6	1.822	0.4
Saving habit	No			
	Yes	0.3	1.349	0.3
Practice irrigation	No			
	Yes	-0.3	0.712	0.4
Size of the land in hectares	Less than 1.6 hectares			
	1.6 to 2 hectares	-0.1	0.905	0.3
	Greater than 2 hectares	0.4	1.492	0.4
Have they taken a loan?	No			
	Yes	-0.4	0.670	0.3
Size of the tropical livestock	Less than 2.5			
	Greater or equal to 2.5	0.4	1.492	0.3
Use of improved seed on the farm	No			
	Yes	-0.2	0.818	0.3
Soil fertility of the agricultural land	Infertile			
	Fertile	0.3	1.349	0.4
Use of fertilizer	No			
	Yes	0.5	1.648	0.4
Ownership nature of the land	Rent/lease			
	Private	-0.2	0.818	0.3

Convergence and Accuracy of the Model

Time series plots and density plots along with autocorrelation plots were used to evaluate convergence. The plots below show that the algorithm’s convergence achieved in every plot of significant predictors.

Time Series Plots

Figures 1 to 5 show the convergence time series plots for gender (male), age, educational and marital status, and religion for the coefficients in the FS data. These plots display a good mixture of the chains as the four independently generated chains mixed.

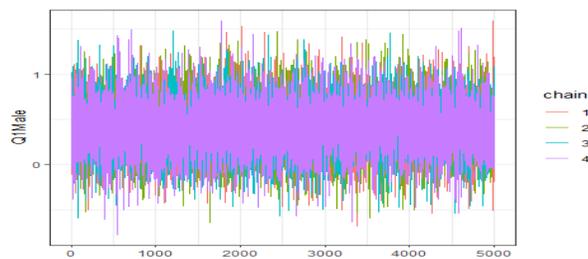


Figure 1. Convergence of time series plot for gender (male).

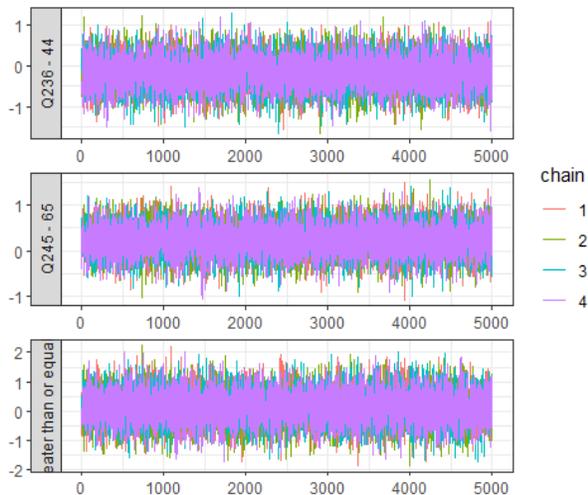


Figure 2. Convergence of time series plot for age of the household head.

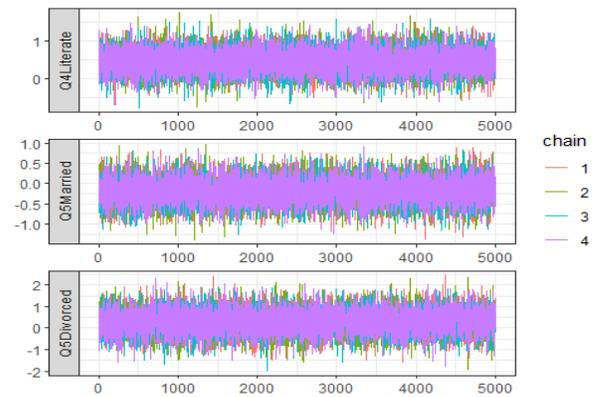


Figure 3. Convergence of time series plot, educational and marital status.

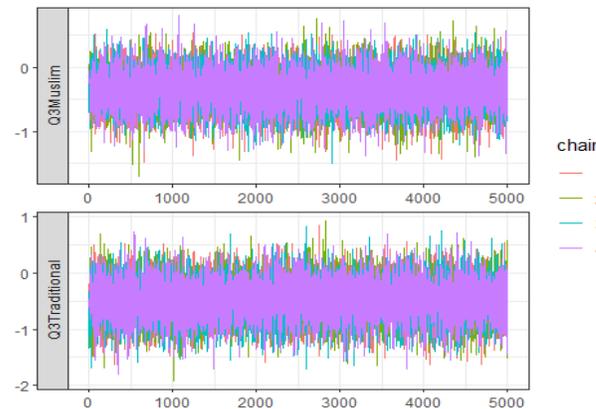


Figure 4. Convergence of time series plot, religion of the household.

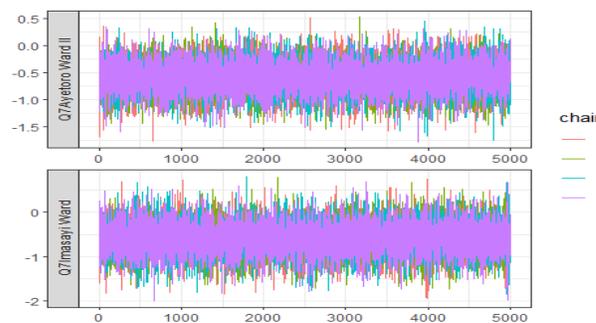


Figure 5. Convergence of time series plot, ecological zones.

Autocorrelation Plot

The plots in Figures 6 and 7 show evidence of convergence as the four independent chains overlapped each other and faded with longer delays.

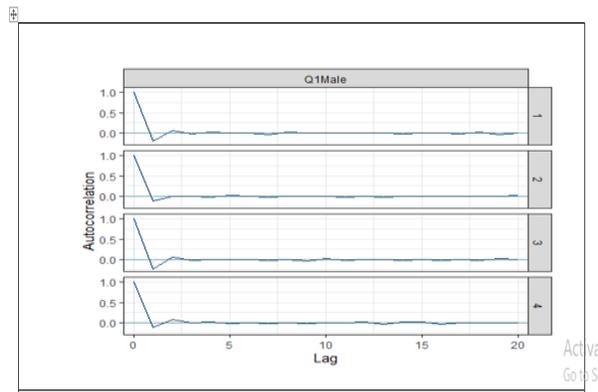


Figure 6. Convergence based on autocorrelation plot for gender (male).

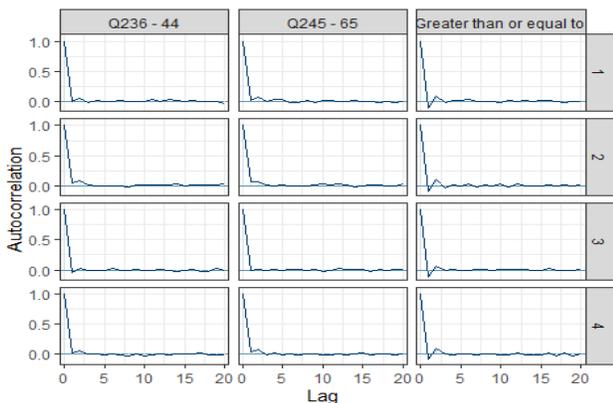


Figure 7. Convergence based on autocorrelation plot for age.

Density Plot

Figures 8 and 9 show the density plots of selected parameters in the FS analysis data. The simulated parameter values indicated convergence since the plots for most predictor variables indicated that the coefficient has a normal distribution.

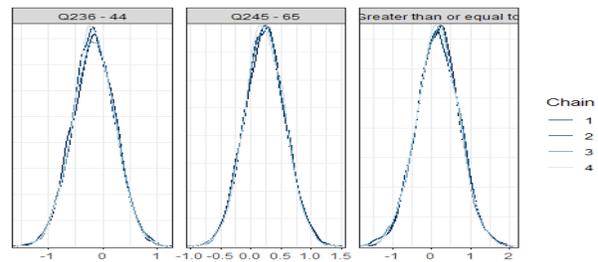


Figure 8. Convergence for density plot for age.

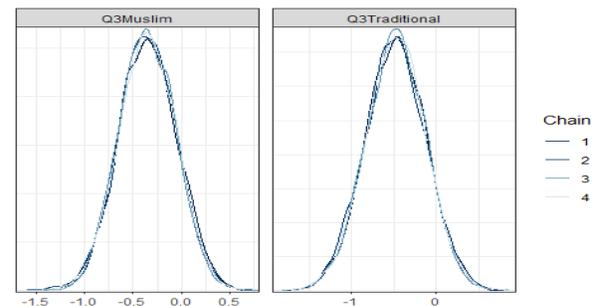


Figure 9. Convergence for density plot for religion.

DISCUSSION OF RESULTS

The rate of FI among households in the designated local government area was assessed in this study, along with important drivers that contribute to this situation. Logistic regression via Bayesian inferences was utilized to identify major factors contributing to FI such as gender disparities, family size, land usage, and financial support employing Gibbs sampler algorithm. The Gibbs sampler was employed because of its effectiveness in its implementation and high acceptance rates and suitability for conjugate priors for Bayesian logistics regression. The study also found that a household’s level of FI is significantly predicted by the gender and age of the head of the household, which may differ by culture. The outcome promotes education (awareness) regarding reduced birth rates in order to decrease the size of families. According to the results, the head of the household’s marital status was a significant predictor of their level

of FI status was also significantly predicted by the household's tropical livestock unit. Compared to households with few livestock units, those with more tropical livestock units had a lower likelihood of experiencing FI. The study found a significant correlation between FI and farmland soil fertility.

Households with fertile soil recorded a higher likelihood of FS; this can be traced to results emerging from increased agricultural productivity that comes with farming on fertile soil. The respondents' loan status was another important determinant of their level of FI.

FI was more common among households without a loan from any financial institution than among those with a loan. This suggests that households without loans have a greater probability to experience FI than households with loans. This might be the case because borrowers can raise their income and use it to buy livestock and agricultural inputs.

CONCLUSIONS

This study reveals that 60.3% of households in Yewa-North Local Government Area in western Ogun State, Nigeria, are affected by FI, a significant concern. Female-headed households face higher FI, indicating a need for gender-specific interventions. Older household heads generally experience less FI, suggesting that leveraging their experience could be beneficial. Larger families tend to have more FI, highlighting the need for family size management. Married individuals seem to have better FS, potentially due to additional support, so unmarried households may need more support. Households with larger farms, land ownership, and fertile soil are less expected to be food insecure, emphasizing the importance of land and agricultural management. More livestock units are linked to better FS, indicating that supporting livestock farming can help. Access to loans is associated with improved FS, making financial support crucial.

Overall, targeted strategies addressing these factors could effectively reduce FI in the area. Also, targeted interventions that address these specific predictors such as gender disparities, family size, land usage, and financial support could be effective in reducing FI in the local government area.

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