Watsala et al. Discover Food (2026) 6:224
https://doi.org/10.1007/s44187-026-00961-6

Discover Food

RESEARCH

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Modeling food security status among beans and maize farming households in Uganda

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Abstract

Food security is a critical pillar of household welfare, yet modeling its determinants is often complicated by over-dispersed data and an excess of food-secure households (zeros). This study identifies the sociodemographic, economic, and institutional drivers of food security among households engaged in bean and maize farming in Uganda, providing evidence for targeted resilience-building policies. Using secondary data from the National Agricultural Research Organization (NARO) Impact Evaluation Survey ($n = 1,428$), food security was measured as the Household Food Insecurity Access Scale (HFIAS), a nine-item experiential tool (0–27). To address the high proportion of zeros representing both "structurally" secure and "period-secure" households, a multivariate Zero–Inflated Negative Binomial (ZINB) regression was employed. This two-part framework technically justifies the distinction between the drivers of permanent food security and the drivers of insecurity severity. Although HFIAS is a bounded sum, post-estimation diagnostics confirmed the model's appropriateness for this sample, with 100% of scores falling within the 0–22 range, avoiding "boundary leakage." Model robustness was further validated using the Likelihood Ratio tests of alpha, the Vuong test, and Rootogram diagnostics. Results are reported as Incidence Rate Ratios (IRRs) for the count process and coefficients for the inflation process. The count model revealed that higher education level (Secondary IRR = 0.68; Tertiary IRR = 0.63, ($p < 0.01$) and larger farm size (IRR = 0.98, ($p = 0.012$) significantly reduced the intensity of food insecurity. Conversely, being widowed or divorced (IRR = 1.41, $p = 0.043$) and residing in the Western region (IRR = 1.27, $p = 0.008$) significantly increased insecurity severity. The inflation model demonstrated that tertiary education and farm size were primary predictors of "structural food security," significantly increasing the probability of a household being consistently food secure. Food security in Uganda is driven by a two-stage process where the level of education and land assets govern both long-term resilience and the intensity of hunger shocks. Policymaking should pivot toward region-specific, literacy-sensitive interventions and social protection for widowed heads of households. Strengthening secondary education and addressing land fragmentation are essential to moving smallholders beyond transient security toward structural resilience.

Keywords Food security, Household Food Insecurity Access Scale (HFIAS), Zero-Inflated Negative Binomial (ZINB) Regression, Uganda smallholder farmers, Resilience policy

1 Background

Food security is a multidimensional construct occurring when all people, at all times, have physical, social, and economic access to sufficient, safe, and nutritious food that meets their dietary needs and preferences for an active and healthy life [13]. Historically, food security measurements focused primarily on the "availability" pillar, national-level caloric supplies, and food production. However, contemporary frameworks emphasize the "access" pillar, acknowledging that food insecurity often stems from a household's inability to acquire food due to economic or social constraints rather than a lack of aggregate supply [35].

Globally, over 870 million people experience food insecurity. Admasu, [3], with Sub-Saharan Africa, including Uganda, being the most affected region. In Uganda, an estimated 2.6 million people are food insecure, with 17% classified in crisis. Akwango-Aliau et al. [5]. Understanding the factors that influence household food security is vital for guiding evidence-based agricultural, social protection, and development policies.

Several empirical studies across different settings have documented similar determinants of household food security, including education, farm size, fertilizer and improved seed use, access to credit, and membership in a farmer group, providing cross-country evidence from Rwanda, Ethiopia, Nigeria, South Africa, Swaziland, and Pakistan [1, 2, 7, 16, 18, 22, 25, 27, 28]. Comparative reviews also stress system-level drivers and shock responses that interact with household determinants [10, 11, 17]. Measurement critiques relevant to our analytic choice suggest that dichotomization or categorization of continuous food security measures incurs important statistical costs [6, 15] while debates on dietary diversity as an indicator are summarized by [34].

In Uganda, previous studies have examined the drivers of food security from various perspectives. For instance, [36] highlighted the vulnerability of smallholders to climate variability, while (Apanovich et al. 2018) demonstrated how legume-based systems and institutional support enhance household resilience. However, these studies primarily utilize categorical or binary indicators of food security, which may fail to capture the nuanced intensity of the food insecurity experience among bean and maize farmer groups that provide the bulk of the country's dietary protein and calories but remain highly susceptible to seasonal shocks.

To capture the "access" dimension of food security, researchers employ various experiential tools. Unlike objective indicators like caloric intake or anthropometric data, which can be costly and fail to capture psychological and behavioral components, experiential scales provide a validated measure of how households actually perceive and navigate food scarcity. This study utilizes the Household Food Insecurity Access Scale (HFIAS), a nine-item tool developed by USAID's Food and Nutrition Technical Assistance (FANTA) project (Coates et al. 2007; [12]). The HFIAS captures three universal domains of food insecurity: anxiety and uncertainty about food supply, insufficient food quality, and inadequate food intake. Because the HFIAS produces a continuous-like score (0–27), it allows for a granular analysis of food insecurity intensity rather than simple categorizations.

Despite the granularity of the HFIAS, most studies model the outcome as a binary variable (using logistic regression) or an ordered variable (using ordered logit/probit models) [1, 29]

Categorization results in a loss of information and reduced statistical efficiency, obscuring variation in household behaviors. Altman and Royston, [6], Kyomuhangi, [21]. A more robust approach is to model the HFIAS as a bounded count variable. However, HFIAS data typically exhibits two specific statistical challenges: a high proportion of food-secure households (excess zeros) and variance that significantly exceeds the mean (overdispersion).

This study addresses these challenges by employing a Zero-Inflated Negative Binomial (ZINB) regression model. This approach is conceptually grounded in the existence of two distinct groups within the zero-score category: "structural zeros" (households fundamentally secure due to stable socioeconomic factors) and "sampling zeros" (households at risk that remained secure during the 30-day recall period). By using a two-part model (logit for structural security and negative binomial for intensity), we simultaneously identify the drivers of being food secure and the factors influencing the severity of insecurity among vulnerable households, while specifically adjusting for the overdispersion that simpler Poisson-based models cannot capture [15, 19].

Furthermore, existing literature often overlooks the dual nature of food-secure households in the Ugandan context, failing to distinguish between those who are structurally resilient and those who are incidentally secure. This study fills these gaps by employing a Zero-Inflated Negative Binomial (ZINB) model. By modeling the HFIAS as a bounded count outcome and accounting for excess zeros and overdispersion, we provide a more precise identification of the sociodemographic, economic, and institutional factors that influence both the likelihood of being food secure and the severity of insecurity among beans and maize farming households. These two crops are not merely staples but are twin pillars for rural-dependent households. Consequently, this study provides evidence to guide targeted, context-specific interventions.

2 Methods

2.1 Sampling design and sample size

A multistage sampling design was used to select respondents on the basis of agroecological zones, districts, sub-counties, and villages. In the first stage, six out of nine agroecological zones were selected on the basis of whether they directly participated in NARO technology development and/or dissemination, for this case, at the level of adoption and utilization of NARO-released maize and bean technologies in Uganda. At the second stage of sampling, a total of thirty districts were selected from the six selected agroecological zones via cluster sampling on the basis of the level and intensity of promotional outreach activities. In the third stage, two sub-counties in each of the districts were randomly selected. Finally, farming households in each of the sub-counties were selected using stratified random sampling from the list of participating farmer households available with the respective Zonal Agricultural Research and Development Institutes (ZARDIs) and District Agriculture Offices (DAOs). A total of 1,445 households, representing 65% of the sample size, responded to the study [5].

2.2 Data source and collection period

This study utilized secondary data from the NARO Impact Evaluation Survey. The NARO dataset was selected due to its robust sampling frame of bean and maize farming households across Uganda's Agro zones, providing a representative look at the demographics most critical to national food security. The data were collected during Quarter two of the FY 2021/22, a period purposefully chosen to capture household experiences following the primary harvest season.

This timing was critical as it allowed for an assessment of food access stability during the transition into the lean season, providing a rigorous test of household resilience and storage capabilities.

2.3 Model selection and validation

For appropriate model selection, the Zero-Inflated Negative Binomial (ZINB) model was benchmarked against a Cragg's Double Hurdle (DH) model. While both frameworks accommodate a two-stage process, distinguishing between the 'probability' of being food secure and the 'intensity' of insecurity, information criteria and diagnostic tests were used to determine the superior fit.

The model Statistical fitness check and validation (Table 1) revealed that the ZINB model yielded lower Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values compared to the Double Hurdle model. This indicates that the Negative Binomial distribution better handles the overdispersion inherent in the HFIAS count data than the truncated normal distribution.

The Zero-Inflated Negative Binomial (ZINB) regression model was then fitted to examine the factors associated with food security status among bean and maize farming households in Uganda. By incorporating a dispersion parameter (α), the ZINB model more accurately estimates standard errors and prevents the overstatement of statistical significance common in Poisson-based models when heteroskedasticity is present [19].

Following the specification by (Freese et al., 2014) The model is described as:

$$P\left(Y_i \mid X_i\right) = \begin{cases} \rho_i + (1-\rho_i)\left(\frac{1}{1+\alpha\mu_i}\right)^{1/\alpha}, & \text{for } y_i = 0, \\ (1-\rho_i)\,\frac{\Gamma(y_i+1/\alpha)}{\Gamma(y_i+1)\,\Gamma(1/\alpha)}\left(\frac{1}{1+\alpha\mu_i}\right)^{1/\alpha}\left(\frac{\alpha\mu_i}{1+\alpha\mu_i}\right)^{y_i}, & \text{for } y_i > 0. \end{cases}$$

where:

- Y_i is the HFIAS count response, bounded such that $0 \le y_i \le 27$
- ρ_i is the probability of the household being a "structural zero" (consistently food secure), modeled via a logit link: $logit\left(\rho_i\right) = u_i^T \beta_u$
- μi is the expected HFIAS score for the at-risk group, modeled via a log link: $\ln\left(\mu_i\right) = v_i^T \beta_v$
- α is the dispersion parameter. When $\alpha > 0$, the model accounts for overdispersion; as $\alpha \to 0$, the ZINB reduces to a ZIP model.

Table 1 Model fitness and validation criterion

Diagnostic metric	ZINB model	DH model
AIC	4536.766	4688.444
BIC	4731.535	4841.101

- u_i and v_i are vectors of explanatory variables (socio-demographic, economic, and institutional) that may overlap or differ between the two components.

2.4 Model diagnostics

The goodness-of-fit of the ZINB model was assessed using a suite of diagnostic tests to ensure the reliability and effectiveness of the estimates. The overall significance of the model was evaluated using the Likelihood Ratio (LR) Chi-square test, testing the null hypothesis that all predictor variables are simultaneously equal to zero. Statistical significance was set at the 5% level ($p < 0.05$). The Likelihood Ratio test of alpha (α) was conducted to assess the presence of overdispersion. A significant result ($p < 0.05$) indicates that the dispersion parameter is significantly different from zero, confirming that the ZINB model is necessary to account for the variance instability and heteroskedasticity inherent in the HFIAS data.

To test for the necessity of the zero-inflation component, the Vuong test was employed. (Vuong, 1989), comparing the ZINB against a standard Negative Binomial model to determine if the "structural zero" mechanism significantly improves the model's predictive power.

Finally, residual diagnostics were utilized to evaluate the quality of the fit. Given that traditional tests for heteroskedasticity, such as the Breusch-Pagan and White tests, are designed for linear models and are not directly applicable to nonlinear count processes, we employed the Rootograms. This method allowed for a visual assessment of the model's ability to handle the bounded nature of the HFIAS scale (0–27). The link specification test (linktest) was also performed to verify that the log and logit functions were correctly specified, with a non-significant result on the squared predictor variable confirming appropriate model specification.

3 Results

The goodness-of-fit of the Zero-Inflated Negative Binomial (ZINB) model was assessed using a suite of diagnostic tests to ensure the reliability and effectiveness of the estimates.

The overall significance of the model was evaluated using the Likelihood Ratio (LR) Chi-square test, which yielded a value of Chi2(17) = 67.20 (p-value 0.000), leading to the rejection of the null hypothesis that all predictor variables were simultaneously equal to zero. The Likelihood Ratio test of alpha (α) resulted in a significant value of Chibar2(01) = 323.91 (p-value 0.000). This significant result indicates that the dispersion parameter is significantly different from zero, confirming that the ZINB model is necessary to account for the variance instability and heteroskedasticity inherent in the HFIAS data. Furthermore, to specifically test for the necessity of the zero-inflation component, the Vuong test was employed. The resulting z-statistic of (10.66) ($p = 0.000$) confirms that the "structural zero" mechanism significantly improves the model's predictive power. This was validated by the lower AIC (4536.766) and BIC (4731.535) statistics for the ZINB compared to the higher AIC (4688.444) and BIC (4841.101) for the DH model.

Finally, residual diagnostics were utilized to evaluate the quality of the fit. Visual assessment through Rootograms demonstrated that the model effectively managed the bounded nature of the HFIAS scale (0–27), with predicted values closely aligning with observed frequencies. The link specification test (linktest) yielded a non-significant result on the squared predictor variable (P-value = 0.000), confirming that the log and logit functions were correctly specified and that the model does not suffer from omitted variable bias.

Description of sample characteristics of the Respondents (Table 2).

The mean age of the household heads was 46.8 years (SE 0.34). There was 78.3% male headed households, and only 21.7% of them were female-headed. The majority, 96.9% of the household heads, had achieved at least Primary level of education, and 83.0% were married. On average, there were 7.4 household members both present and absent (SE 0.11) at the time of the survey.

Up to 58.5% of the household heads had at least three years of farming experience, and 55.8% used fertilizer to boost agricultural production. 59.9% used improved NARO maize and bean technology. The majority, 75.7%, owned livestock at the time of the survey, 69.7% had their main source of household income from crop sales, and 62.6% had access to credit. 73.2% were members of the farmers' group, and only 5.6% had access to price-related market information on crops.

The median household food security score was 0, and it ranged from 0 to 4 (IQR: 0–4). The median represents the middle value when all household food security scores

Table 2 Description of the household head farmer characteristics

Characteristics	Level	Freq (n = 1,445)	Percent (100%)
Age (years)	Mean (SE)	46.8 (0.34)	
Gender	Female	314	21.7
	Male	1131	78.3
Education level	No formal education	102	7.1
	Primary education	729	50.4
	Secondary education	475	32.9
	Tertiary education	139	9.6
Marital status	Single	75	5.2
	Married	1200	83.0
	Widowed/or divorced	170	11.8
Household size	Mean (SE)	7.4 (0.11)	
Location of the household	Central	496	34.3
	Eastern	334	23.1
	Northern	408	28.3
	Western	207	14.3
Farming experience	Less than three	599	41.5
	Three and more	846	58.5
Farm size (ha)	Median (IQR)	3.7 (2–6)	
Use of fertilizer	No	639	44.2
	Yes	806	55.8
Use of improved Maize/bean	No	580	40.1
	Yes	865	59.9
Livestock ownership	No	351	24.3
	Yes	1094	75.7
HH's main source of income	Crop income	1007	69.7
	Non-crop income	438	30.3
Access to credit	No	540	37.4
	Yes	905	62.6
Membership in a farmers' group	No	387	26.8
	Yes	1058	73.2
Access to market information	No	1361	94.2
	Yes	84	5.8
Household Food Insecurity Access Scale (HFIAS)	Median (IQR)	0 (0–4)	

SE: Standard Error; IQR: Interquartile range; No.- frequency; %-percent are arranged from lowest to highest. A median of 0 indicates that at least half of the households reported no food insecurity, as measured by the Household Food Insecurity Access Scale (HFIAS).

The range (0–4) reflects the minimum and maximum scores observed in the sample. A range from 0 to 4 shows that no household had a food insecurity score above 4, and some households had no reported food insecurity.

The IQR describes the spread of the middle 50% of the data, from the 25th to the 75th percentile. An IQR of 0 to 4 suggests that most households experienced low levels of food insecurity, though some variation exists within the group. Overall, the data indicate that the majority of households were food secure, with a significant proportion reporting no food insecurity. However, some households did experience mild to moderate food insecurity. This skewed distribution, with many households scoring zero, supports the use of statistical models such as Zero-Inflated Negative Binomial (ZINB) regression, which appropriately handle excess zeros in count data (Fig. 1).

The distribution of HFIAS scores among the sampled households is heavily skewed, with a high frequency of zero scores indicating households with full food access (see Fig 1). This significant zero inflation in the dependent variable supports the use of the ZINB model to account for the structural zero mechanism.

Results of factors associated with the Household Food Insecurity Access Scale based on a multivariate ZINB.

The ZINB regression model output has both the count model (upper part in Table 3) and a logit model (lower part in Table 3) for predicting excess zeros.

The following remarks are based on the count model, Determinants of the Frequency of Food Insecurity, for the significant factors only.

Education of the household head was a significant predictor of household food security. Relative to households with no formal education, those headed by individuals with

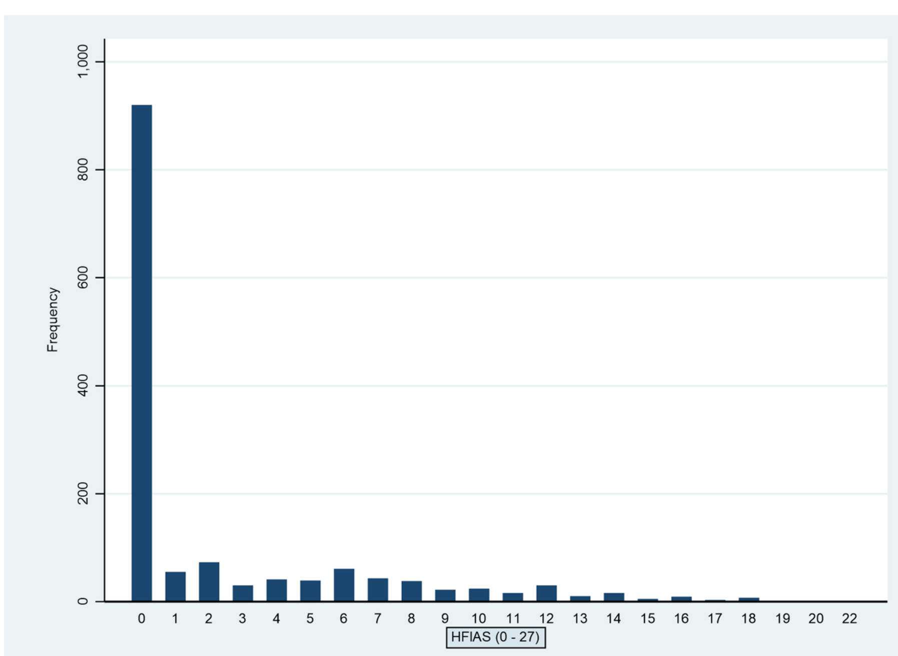

Fig. 1 Frequency of occurrence of conditions hindering household food access against the household food insecurity score

Table 3 Results of factors associated with the household food insecurity access scale based on a multivariate zero-inflated negative binomial

HFIAS (outcome)	IRR	St. Err.	*p* value	95% CI
Gender				
Female✓	1			
Male	1.13	0.12	0.241	0.92–1.38
Education level				
No formal education✓	1			
Primary	0.83	0.10	0.113	0.65–1.05
Secondary	0.68	0.09	< 0.004**	0.53–0.88
Tertiary/higher	0.63	0.11	< 0.007**	0.45–0.88
Marital status of household head				
Single✓	1			
Married	1.24	0.18	0.159	0.92–1.66
Widowed/divorced	1.41	0.24	0.043*	1.01–1.95
Household size	0.99	0.09	0.259	0.97–1.00
Region				
Central✓	1			
Eastern	1.22	0.14	0.094	0.96–1.53
Northern	1.05	0.100	0.605	0.87–1.27
Western	1.27	0.11	< 0.008**	1.06–1.51
Farming experience				
Less than three years✓	1			
Three and more	1.09	0.07	0.181	0.96–1.25
Farm size (ha)	0.98	0.08	< 0.012**	0.96–0.99
Use of fertilizer to boost production				
No✓	1			
Yes	0.88	0.06	0.072	0.76–1.01
Use of improved Maize & Beans				
No✓	1			
Yes	0.91	0.064	0.081	0.79–1.04
Livestock ownership				
No✓	1			
Yes	0.98	0.08	0.766	0.84–1.13
Access to credit				
No✓	1			
Yes	0.90	0.06	0.147	0.79–1.04
Membership in a farmers' group				
No✓	1			
Yes	0.90	0.07	0.184	0.78–1.05
Constant	7.70	1.56	0.000***	5.17–11.45
Inflate				
Gender				
Female✓	1			
Male	0.04	0.21	0.849	−0.37–0.44
Education level				
No formal education✓	1			
Primary	0.41	0.25	0.096	−0.07–0.89
Secondary	0.42	0.26	0.109	−0.09–0.93
Tertiary/higher	0.87	0.32	< 0.008***	0.23–1.51
Marital status of household head				
Single✓	1			
Married	0.22	0.30	0.470	−0.38–0.81
Widowed/divorced	0.30	0.32	0.357	−0.34–0.95
Household size	−0.01	0.02	0.451	−0.05–0.02

Table 3 (continued)

HFIAS (outcome)	IRR	St. Err.	*p* value	95% CI
Model summary				
Number of observations	1,428			
Non-zero observations	518			
Zero observations	910			
LR chi2(17)	67.20			
Prob > chi2	0.000***			
Log-likelihood	−2231.383			

Significance: ***$p = 0.000$, **$p < 0.05$, *$p < 0.1$; 95% CI-confidence intervals; ✓-Reference categories adopted in the analysis for categorical variables; Std. Err. - Standard error; IRR-Incident rate ratio

secondary education experienced a 32% reduction in the expected frequency of food insecurity (IRR = 0.68, p = 0.004), while those with tertiary or higher education exhibited a 37% reduction (IRR = 0.63, p = 0.007). These findings are consistent with prior research demonstrating that education improves agricultural decision-making, income diversification, and nutritional awareness, which collectively enhance household food security. [9, 37]. Education also enhances access to extension services and adoption of yield-enhancing technologies, thereby reducing vulnerability to food shortages.

Marital status was significantly associated with household food security. Compared with single household heads, widowed or divorced household heads were 40% more likely to be food secure, as reflected by a lower expected frequency of food insecurity (IRR = 1.41, $p = 0.043$). This finding may reflect the buffering role of social capital and extended family networks that support widowed individuals, helping them navigate economic and emotional challenges [23]. Such support can facilitate stability in food access despite household restructuring following the loss of a spouse.

Regional location significantly influenced food security outcomes. Households in the Western region were 26% more likely to be food secure compared with those in the Central region (IRR = 1.27, $p = 0.008$).

Farm size was also significant in predicting food security. Each additional acre of cultivated land decreased the expected frequency of food insecurity by 2% (IRR = 0.98, $p = 0.012$).

The following observations are based on the inflated model (lower part in Table 3) for predicting excess zeros.

In the zero-inflation component, tertiary education significantly increased the likelihood of a household being structurally food secure, meaning they experienced no food insecurity during the recall period (β = 0.87, $p = 0.008$).

Regional disparities also appeared in the structural food security model. Households in the Eastern (β = 0.78, $p < 0.001$) and Western (β = −1.70, $p < 0.001$) regions differed significantly from those in the Central region in terms of the probability of belonging to the always-food-secure group. Although households in the Western region showed better relative food security in the count model, they were less likely to be permanently food secure.

Farm size also significantly increased the likelihood of structural food security (β = 0.04, $p = 0.004$). Larger farms not only provide greater production capacity but also stabilize food availability across seasons, offering protection against food insecurity shocks.

4 Discussions

The findings of this study demonstrate that sociodemographic, economic, and institutional characteristics jointly influence food security among bean and maize farming households in Uganda. The Zero-Inflated Negative Binomial (ZINB) model proved superior to standard count models, as the significant alpha parameter ($\alpha = 0.32$, $p < 0.001$) confirmed substantial overdispersion. By distinguishing between "structural resilience" (inflation model) and "insecurity intensity" (count model), the study revealed that determinants often act differently across these two stages.

Socio-demographic determinants, Education level emerged as a primary driver of both structural resilience and reduced insecurity intensity. Households headed by individuals with secondary or tertiary education experienced a 32% to 37% reduction in the expected frequency of food insecurity compared to those with no formal education. These findings are consistent with prior research in Uganda and Ethiopia demonstrating that education improves agricultural decision-making, income diversification, and nutritional awareness [9, 37]. Furthermore, the inflation model showed that tertiary education significantly increased the likelihood of a household being structurally food secure ($\beta = 0.87, p = 0.008$), reinforcing the role of higher education level in ensuring long-term financial stability and risk management [4, 30].

In terms of household structure, widowed or divorced status significantly increased the intensity of food insecurity by 41% (IRR = 1.41, $p = 0.043$) compared to single individuals. While some global studies suggest social capital can buffer these groups [23], Our results suggest that in the context of Ugandan bean and maize farming, the loss of a spouse likely leads to "labor-poverty" and reduced pooled resources, making these households more vulnerable to higher-intensity insecurity shocks.

Economic and Regional Dynamics, Farm size acted as a critical protective factor in both model components. Each additional acre decreased the expected frequency of food insecurity by 2% and significantly increased the likelihood of structural food security ($\beta = 0.04$, $p = 0.004$).

Larger landholdings facilitate crop diversification and higher production capacity, which stabilizes food availability across seasons. Joshi and Joshi, [20, 36]. This underscores the conclusion by [32] that land access remains foundational to household resilience in agrarian settings.

Geographically, the study revealed complex regional disparities. Households in the Western region exhibited a 27% higher intensity of food insecurity (IRR = 1.27, p = 0.008) and were significantly less likely to be structurally food secure ($\beta = -1.70$, $p <$ 0.001) compared to the Central region. Conversely, households in the Eastern region were more likely to belong to the structurally food-secure group ($\beta = 0.78$, $p < 0.001$). These findings suggest that, despite favorable Agro-ecological conditions in parts of the West, underlying vulnerabilities such as market disruptions or seasonal crop failures may still hinder permanent food security [8, 14, 38].

5 Conclusion

This study provides decisive evidence that household food security among Uganda's bean and maize farmers is not merely a product of agricultural yield but is fundamentally rooted in the education level, land equity, and regional resilience. By employing a Zero-Inflated Negative Binomial (ZINB) model, we have demonstrated that the drivers of structural food security differ profoundly from the factors governing the intensity of hunger. Education and farm size emerged as the dual pillars of resilience: higher education level and larger landholdings do not just reduce the severity of food insecurity; they fundamentally insulate households, moving them into a state of permanent, structural security.

The findings expose a critical vulnerability among widowed and divorced household heads and those residing in the Western region, who face significantly higher intensities of food insecurity. These disparities suggest that current “one-size-fits-all” agricultural interventions are failing to account for the labor-poverty and geographic inequities that characterize rural Uganda. Furthermore, the lack of significant impact from credit access and farmer group membership in our multivariable model indicates that institutional support systems may be currently underperforming or inaccessible to the most vulnerable smallholders.

6 Recommendations

The study recommends that the Government of Uganda, with its joint stock of development partners, must pivot toward literacy-sensitive, asset-based, and region-specific interventions. First, education must be treated as a primary food security tool; expanding secondary and vocational training is essential for long-term household stability. Second, targeted social protection programs should be developed for widowed and divorced household heads. Our findings indicate that marital status is a significant determinant of food security; therefore, policy interventions should aim to replicate the ‘pooled resource’ benefits typically found in married households for the widowed/divorced. By providing targeted support to these specific groups, interventions can mitigate the increased vulnerability associated with household restructuring and ensure more stable food access. Finally, agricultural policies must move beyond the simple provision of inputs to address the structural barriers, such as land fragmentation and regional market volatility, that prevent farmers from translating harvests into sustainable food access. Only by addressing these deep-seated sociodemographic and economic determinants can Uganda build a food system resilient enough to withstand the climatic and economic shocks of the coming decade.

Abbreviations

AIC	Akaike Information Criterion
BIC	Bayesian Information Criterion
COBAMS	College of Business and Management Science
DAOs	District Agriculture Offices
DH	Double hurdle model
FAO	Food and Agriculture Organization
FANTA	Food and Nutrition Assistance Project
FCS	Food Consumption Score
HDDS	Household Dietary Diversity Score
HHs	Households
HFIAS	Household Food Insecurity Access Scale
IRR	Incident rate ratio
NARO	National Agricultural Research Organization
SSP	School of Statistics and Planning
UNSCT	Uganda National Council for Science and Technology
ZARDI	Zonal Agricultural Research and Development Institutes
ZINB	Zero-Inflated Negative Binomial Regression model

Acknowledgements
Not applicable.

Author contributions
"D.W. and F.W. contributed to Conceptualization, Methodology, Software, Validation, Formal Analysis, Investigation, Resources, Data Curation, Writing - Original Draft, Writing - Review & Editing, Visualization, Project administration & Funding acquisition.JB.A. Contributed to Methodology, Validation, Investigation, Writing - Review & Editing, Visualization, and Project administration.F.W. and JB.A. both contributed to Supervision."

Funding
Not applicable.

Data availability
The Impact evaluation survey data that support the findings of this study are available from the NARO, but restrictions apply to the availability of these data, which were used under license for the current study, and so are not publicly available. Data are, however, available from the authors upon reasonable request and with permission of the NARO.

Declarations

Ethics approval and consent to participate
Ethical clearance for the primary survey was obtained from the National Agricultural Research Organization (NARO) Research and Ethics Committee and formally registered with the Uganda National Council for Science and Technology (UNCST). The NARO granted permission to utilize the secondary dataset for this study. This study was conducted in accordance with the ethical principles of the Declaration of Helsinki. To uphold respondent confidentiality and privacy, all data were fully anonymized before analysis. This study utilized secondary household-level data from the National Agricultural Research Organization (NARO) Impact Evaluation Survey. The original data collection was conducted in accordance with ethical standards, and informed consent was obtained from all participants.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

Received: 20 October 2025 / Accepted: 25 March 2026
Published online: 02 April 2026

References

1. Abdullah, Zhou D, Shah T, Ali S, Ahmad W, Din IU, Ilyas A. Factors affecting household food security in the rural northern hinterland of Pakistan. J Saudi Soc Agricultural Sci. 2019;18(2):201–10. https://doi.org/10.1016/j.jssas.2017.05.003.
2. Abegaz KH. Determinants of food security: evidence from the Ethiopian Rural Household Survey (ERHS) using a pooled cross-sectional study. Agric Food Secur. 2017;6(1):1–7. https://doi.org/10.1186/s40066-017-0153-1.
3. Admasu A. Determinants of Food Security Status in Rural Households in Mojaena Wodera Woreda, Ethiopia. Am J Theoretical Appl Stat. 2019;8(2):67. https://doi.org/10.11648/j.ajtas.20190802.13.
4. Ahmed F, Abah P. Determinants of food security among low-income households in Maiduguri Metropolis of Borno State, Nigeria. Asian J Social Sci Humanit. 2014;3(1):74–86. http://www.ajssh.leena-luna.co.jp/AJSSHPDFs/3(1)/AJSSH2014(3.1-10).pdf.
5. Akwango-Aliau D, Lukwago G, Ariong RM, Kiyingi I, Obongo I, Adur S, Angundupo S, Ndhokero J, Luzinda H, Akongo T, Magala D, Mutonyi S, Bwanika G, Ambrose A, Yona B, Bua A. Impact of NARO Bean and Maize Technologies. on Farmer Livelihoods and Contribution to Uganda's Economy; 2022.
6. Altman DG, Royston P. The cost of dichotomizing continuous variables. BMJ. 2006;332(7549):1080. https://doi.org/10.1136/bmj.332.7549.1080.
7. Amaza PS, Umeh JC, Helsen J, Adejobi AO. Determinants and Measurement of Food Insecurity in Nigeria: Some Empirical Policy Guide (Issue September 2002). Int Association Agricultural Economists. 2006. https://doi.org/10.22004/AG.ECON.25357.
8. Anila Sultana. Determinants of food security at the household level in Pakistan. Afr J Bus Manage. 2011;5(34):12972–9. https://doi.org/10.5897/ajbm11.1441.
9. Awoke W, Eniyew K, Agitew G, Meseret B. Determinants of food security status of household in Central and North Gondar Zone, Ethiopia. Cogent Social Sciences. 2022. https://doi.org/10.1080/23311886.2022.2040138.
10. Béné C, Frankenberger T, Nelson S, Constas M, Collins G, Fox E, et al. Food system resilience measurement: principles, framework, and caveats. Food Secur. 2023;15(6):1437–58. https://doi.org/10.1007/s12571-023-01407-y.
11. Bower T, Presnall C, Frankenberger T, Smith L, Brown V, Langworthy M. Shocks, resilience capacities, and response trajectories over time. FSN Network/TANGO International. 2016. https://www.technicalconsortium.org/wp-content/uploads/2016/02/Report-6-Shocks-Resilience-Capacities-and-Response_18FEb2016.pdf
12. Deitchler M, Ballard T, Swindale A, Coates J. Validation of a Measure of Household Hunger for Cross-Cultural Use (Washington, DC: Food and Nutrition Technical Assistance II Project (FANTA-2), AED, 2010) (Issue May 2010). 2010.
13. FAO. The State of Food Insecurity in the World. 2009.
14. FAO. The State of Food Insecurity in the World. 2018.
15. Fedorov V, Mannino F, Zhang R. Consequences of dichotomization. Pharm Stat. 2009;8(1):50–61. https://doi.org/10.1002/pst.331.
16. Feleke ST, Kilmer RL, Gladwin CH. Determinants of food security in Southern Ethiopia at the household level. Agric Econ. 2005;33(3):351–63. https://doi.org/10.1111/j.1574-0862.2005.00074.x.

17. Frankenberger T, Langworthy M, Spangler T, Nelson S. Enhancing Resilience to Food Security Shocks (Draft White Paper). TANGO International. 2012. https://www.technicalconsortium.org/wp-content/uploads/2014/05/Enhancing-Resilience-to-Food-Security-Shocks_White-paper1.pdf,
18. Habyarimana J. Farmer group membership and food security in Rwanda. Afr J Agric Econ. 2015;10(2):45–56.
19. Hardin JW, Hilbe JM. Generalized estimating Eq. 2nd ed. Chapman and Hall/CRC; 2018.
20. Joshi G, Joshi N. Determinants of household food security in the eastern region of Nepal. SAARC J Agric. 2017;14(2):174–88. https://doi.org/10.3329/sja.v14i2.31257.
21. Kyomuhangi I, Abeku TA, Kirby MJ, Tesfaye G, Giorgi E. Understanding the effects of dichotomization of continuous outcomes on geostatistical inference. Spat Stat. 2021;42(xxxx):100424. https://doi.org/10.1016/j.spasta.2020.100424.
22. Mabuza ML, Ortmann GF, Wale E, Mutenje MJ. The effect of major income sources on rural household food (in)security: evidence from Swaziland and policy implications. Ecol Food Nutr. 2016;55(2):209–30. https://doi.org/10.1080/03670244.2015.1121482.
23. Magaña-Lemus D, Ishdorj A, Rosson CP, Lara-Álvarez J. Determinants of household food insecurity in Mexico. Agric Food Econ. 2016. https://doi.org/10.1186/s40100-016-0054-9.
24. Mathew AC, Siby E, Tom A, Kumar R S. Applications of proportional odds ordinal logistic regression models and continuation ratio models in examining the association of physical inactivity with erectile dysfunction among type 2 diabetic patients. Physical Activity and Nutrition. 2021;25(1):30–4. https://doi.org/10.20463/pan.2021.0005.
25. Mazenda A, Molepo N, Mushayanyama T, Ngarava S. The invisible crisis: the determinants of local food insecurity in Gauteng municipalities, South Africa. Br Food J. 2022;124(13):274–89. https://doi.org/10.1108/BFJ-11-2021-1234.
26. Muche M, Endalew B, Koricho T. Determinants of household food security among Southwest Ethiopia Rural Households. Food Sci Technol. 2014;2(7):93–100. https://doi.org/10.13189/fst.2014.020701.
27. Muhammad NA, Sidique SFB. Determinants of food security among households in Nigeria. Pak J Nutr. 2019;18(11):1042–52. https://doi.org/10.3923/pjn.2019.1042.1052.
28. Ngema PZ, Sibanda M, Musemwa L. Household food security status and its determinants in Maphumulo local municipality, South Africa. Sustain (Switzerland). 2018;10(9):1–23. https://doi.org/10.3390/su10093307.
29. Nkomoki W, Bavorová M, Banout J. Factors associated with household food security in Zambia. Sustain (Switzerland). 2019;11(9):1–18. https://doi.org/10.3390/su11092715.
30. Obayelu AE. Households' food security status and its determinants in North-Central Nigeria. Food Econ. 2012;9(4):241–56. https://doi.org/10.1080/2164828x.2013.845559.
31. Owino V, Lwanga F, Wanyenze RK, Matovu JKB, Orach G, C. Food security and nutritional status of children residing in sugarcane growing communities of East-Central Uganda: A cross-sectional study. J Food Secur. 2015;3(2):34–9.
32. Pender J, Gebremedhin B. Land use, land tenure, and food security in Ethiopian highlands. World Dev. 2008;36(11):1773–86.
33. Penuelas J, Coello F, Sardans J. Better use of fertilizers is needed for global food security and environmental sustainability. Agric Food Secur. 2023;12(1):1–9. https://doi.org/10.1186/s40066-023-00409-5.
34. Ruel MT. Is dietary diversity an indicator of food security or dietary quality? A review of measurement issues and research needs. FoodNutr Bull. 2003;24(2):231–2. https://doi.org/10.1177/156482650302400217.
35. Sen, A. Classic work by Amartya Sen in economics/development theory. Poverty and famines: An essay on entitlement and deprivation. Oxford University Press. 1981.
36. Semazzi JB, Kakungulu M. Household determinants of food security in rural Central Uganda. Acad Journals. 2020;16:1245.
37. Sekhampu TJ. Determinants of the food security status of households receiving government grants in Kwakwatsi, South Africa. Mediterr J Soc Sci. 2013;4(1):147–53. https://doi.org/10.5901/mjss.2013.v4n1p147.
38. Sultana A. Regional variations in food security in Pakistan. Pak Dev Rev. 2011;50(3):197–216.
39. Worku C. Determinants of food security status of households in West Gojjam zone, Ethiopia. Food Sci Nutr. 2023. https://doi.org/10.1002/fsn3.3527.
40. Apanovich, N., & Mazur, R. E. (2018). Determinants of seasonal food security among small holder farmers in south-central Uganda. Agriculture and Food Security, 7(1), 87. https://doi.org/10.1186/s40066-018-0237-6
41. Coates, S., Swindale, A., & Bilinsky, P. (2007). Household Food Insecurity Access Scale (HFIAS) for Measurement of household food access: Indicator guide (version 3). Food and Nutrition Technical Assistance Project, Academy for Educational Development https://www.fantaproject.org/sites/default/files/resources/HFIAS_ENG_v3_Aug07.pdf
42. Vuong, Q.H. (1989). Likelihood ratio tests for model selection and non-nested hypotheses. Econometrica, 57(2), 307-333. https://doi.org/10.2307/1912557
43. Freese, J. & Long, J.S., (2014). Regression models for categorical and limited dependent variables using Stata (3rd ed.). Stata Press

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