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Determinants of household food security in rural uganda: perceived needs as key predictors

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Abstract

Background Food insecurity remains a persistent challenge in Sub-Saharan Africa, particularly in rural areas where households depend on subsistence agriculture and face increasing vulnerability to climate shocks. Despite growing research on the topic, many studies rely on isolated or context-specific indicators, limiting comparability and policy relevance. This study addresses that gap by using two widely recognized indicators—the Food Consumption Score (FCS) and the Months of Adequate Household Food Provisioning (MAHFP)—to assess food security among rural households in Uganda's Sembabule district. It had two main objectives: [1] to compare the diagnostic potential of FCS and MAHFP in assessing household food security, and [2] to identify key determinants of food security using binary logistic regression models. Data were collected from 173 households through a two-phase approach combining structured questionnaires and open-ended interviews.

Results The two indicators produced contrasting results: while 41.5% of households were classified as food insecure by FCS, 68.9% were considered food insecure by MAHFP. Binary logistic regression models identified perceived minimum necessary income, rather than actual income, as a stronger predictor of food security. In addition, household-reported challenges such as hunger, insufficient clothing, lack of farmland, and dissatisfaction with water access emerged as significant determinants. These qualitative variables consistently showed stronger explanatory power than many traditional socioeconomic factors.

Conclusions Findings highlight the multidimensional nature of food insecurity and the value of combining standardized indicators with open-ended, perception-based data. Improving access to cultivable land and safe water, as well as integrating local perspectives into rural development strategies, may enhance the effectiveness of food security interventions. The strong predictive power of perceived needs over objective income measures suggests that policies should go beyond income generation to include financial literacy and resource management support. Additionally, agricultural diversification—particularly through integrated crop-livestock systems—can help households strengthen resilience. This study supports the use of participatory approaches that give voice to lived experiences and help uncover priority needs often overlooked in conventional assessments.

Keywords Food security, FCS, MAHFP, Logit model, Household survey, Africa, Uganda, Livelihoods, Rural development, Determinants

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Background

Ensuring universal access to safe, nutritious, and sufficient food for proper nutrition is a key objective of the United Nations' Sustainable Development Goal "Zero Hunger," which was established in 2015. While significant efforts have been made in recent decades to develop strategies and policies aimed at achieving global food security, between 713 and 757 million people—9% of the world's population—were affected by hunger in 2023, according to The State of Food Security and Nutrition in the World 2024. Among world regions, Sub-Saharan Africa remains the most affected, with about 277 million people—23% of its population—experiencing undernourishment that same year [1].

Many of the undernourished people in Sub-Saharan Africa and worldwide are smallholder farmers who rely on agriculture for their livelihoods [2]. According to Saridakis et al. [3], in Uganda, around 75% of the rural population identifies as farmers, meaning that improvements in this sector have a direct impact on nearly three-quarters of the population. Communities in rural areas rely heavily on subsistence farming and livestock rearing. In particular, the agricultural systems found in Uganda's dry corridor—also known as the cattle corridor—are predominantly rain-fed and rely on low-input practices, with limited diversification and, as a result, a reduced capacity to withstand prolonged droughts [4]. Similar conditions are observed in other dryland areas of East Africa, including Kenya's arid and semi-arid lands (ASALs) [5], or the central dry zone of Tanzania (Dodoma region) [6]. Maize is the primary crop grown in the region, serving as a dietary staple and occupying extensive farmlands alongside beans and plantains. This pattern reflects a wider reality across East Africa, where maize occupies a large share of arable land and provides the bulk of calories consumed by rural households [7]. In Uganda, maize is grown by most smallholders under rain-fed conditions and remains highly vulnerable to drought and other climatic shocks [8, 9]. Such dependence also exposes communities to recurrent food crises during periods of drought, as seen in the severe yield losses and shortages that affected Uganda, Kenya, and Tanzania in 2016 [10]. These events illustrate how closely food security in the region is tied to climate variability. It is well known that climate change, through increased frequency and intensity of extreme weather events like droughts and floods, as well as changes in pest prevalence, can negatively impact crop production and yields [11–13]. With climate projections for Sub-Saharan Africa indicating further disruptions in rainfall patterns [14], the future presents significant challenges for these communities.

Food security is a complex and multidimensional issue that requires careful measurement to understand the nuances of the problem. Past studies have found that relying on a single metric can overlook critical aspects of food insecurity [15]. While some definitions focus solely on food availability, research has shown that other traits like access and affordability are equally crucial determinants [16]. As emphasized by Sen's Entitlement Approach [17], food crises often stem not from insufficient supply but from failures in individuals' ability to access food through production, trade, or transfers. Later frameworks, such as that proposed by Maxwell et al. [18], reinforced this view by comparing several common indicators of household food access, showing that each captures different aspects of food insecurity and can yield contrasting classifications of households.

Despite growing attention, access to adequate and nutritious food remains a major challenge across many developing countries, particularly for rural populations, who often face the greatest barriers to food security [19]. In rural Uganda, where the majority of the population relies on subsistence farming, understanding its determinants is essential for designing effective policy interventions [20]. Recent research conducted in Uganda has confirmed the multidimensional nature of food insecurity, showing that household food access results from the combined influence of income, purchasing capacity, and storage ability. Using integrated modelling during the COVID-19 lockdown, Semakula et al. [21] demonstrated that shocks simultaneously affected multiple livelihood components, highlighting the need for holistic analyses such as the one adopted in this study.

Previous research has highlighted the dynamic relationship between chronic poverty and environmental challenges in shaping food insecurity patterns among rural communities in sub-Saharan Africa [22]. This implies that the vulnerability to food insecurity in these settings is often deeply rooted in the complex interplay of socioeconomic and ecological factors. In this regard, Nuvey et al. [23] provide further evidence from Ghana, showing that food insecurity was significantly more prevalent among livestock-dependent households located in drier districts and among those affected by a higher number of adverse agricultural events. Their study illustrates how agroecological vulnerability and farm-level shocks can reinforce each other in undermining household food access. Comparable patterns have been observed in other East African contexts. For instance, recurrent droughts in Kenya's Turkana region have severely affected pastoral livelihoods and intensified household food insecurity, while in Tanzania's Dodoma region, rainfall variability and prolonged dry spells have similarly undermined agricultural productivity and rural resilience [6, 10].

The challenge of food insecurity in this region is a multifaceted phenomenon, rooted in factors such as poverty, limited agricultural productivity, climate change, and lack of access to resources [24]. In Uganda, the rural population, which makes up the majority of the country's population, is particularly susceptible to food insecurity due to their heavy reliance on subsistence agriculture and limited access to markets and social services, among other variables [22, 24]. These challenges are not unique to Uganda but are shared across East Africa, where national frameworks such as Kenya's Vision 2030 and Tanzania's Agricultural Sector Development Programme II (ASDP II) similarly emphasize agricultural resilience, market integration, and poverty reduction as central pathways to strengthen food security.

Prior studies have explored several key factors contributing to food insecurity in rural communities, including household characteristics, socioeconomic status and environmental conditions [24–27]. In this regard, in order to effectively identify the determinants of food security, selecting appropriate indicators is a key step in obtaining meaningful results. Authors like Sambo et al. [28], for instance, highlight the importance of using standardized and validated indicators to reliably assess food access and nutritional adequacy among rural households. However, while there are various scientific studies that explore the determinants of food security in rural Uganda, the indicators used to assess the population's food security status are often tailored specifically to the context of each investigation. Although this approach offers advantages, such as a high degree of contextual adaptation, it significantly limits the comparability of findings across studies. For instance, the research conducted in Uganda's Gomba district by Semazzi & Kakungulu [20] developed a unique monetary-based approach, converting food harvested and income into monetary equivalents and setting a benchmark value for annual household food security. Although innovative, this methodology significantly hampers the comparability of their results with those of other researchers.

Indicators like the Food Consumption Score (FCS) and the Months of Adequate Household Food Provisioning (MAHFP), as proposed by the World Food Programme [29] and Bilinsky & Swindale [30], solve this issue. The widespread use of both standardized indicators across diverse geographical contexts underscores their validity and reliability in capturing the multifaceted nature of food security. These indicators have been extensively used by other researchers to examine the determinants of food security. While some studies rely on a single indicator for assessment —for instance, Acheampong et al. [31] applied the FCS to evaluate the determinants of food security among farm households across Ghana, others integrate multiple standardized indicators to obtain a more comprehensive understanding of the food security situation. In this regard, Matavel et al. [32] used MAHFP together with FCS and HDDS (Household Dietary Diversity Score) indicators to assess the food security situation in Mozambique during the pre-harvest and harvest periods and identify its key drivers. Similarly, Harris-Fry et al. [33] used MAHFP and WDDS (Women's Dietary Diversity Score) to identify determinants of household food security in Bangladesh. Furthermore, Nkomoki et al. [34] examined the determinants of food security among smallholder farmers in southern Zambia combining the use of FCS and HHS (Household Hunger Scale). The simultaneous use of both indicators allows the analysis to capture complementary temporal and qualitative dimensions of household food security. The FCS reflects short-term dietary diversity and consumption frequency, whereas the MAHFP provides a long-term perspective on seasonal food availability and access. Combining them therefore enhances comparability and offers a more comprehensive picture of food security dynamics.

The present study builds on existing knowledge by using a logistic regression model based on socioeconomic variables to investigate the determinants of food insecurity in the rural Ugandan district of Sembabule, employing standardized and widely adopted food security indicators—the Food Consumption Score (FCS) and Months of Adequate Household Food Provisioning (MAHFP)—to identify key influencing factors. In addition to these standardized metrics, the study introduces a novel component by incorporating variables derived from open-ended questions, which captured respondents' self-reported needs and household challenges. This participatory approach allowed for the integration of perception-based qualitative information into the statistical models, providing a richer and more contextualized understanding of the drivers of food insecurity. Therefore, the objectives of this study are twofold: first, to compare the diagnostic potential of FCS and MAHFP for assessing household food security; and second, to identify the key determinants of household food security in rural Sembabule by developing a regression model for both indicators.

Methods

Data collection

The study was conducted in Sembabule district, a predominantly rural area located in the central region of Uganda. A total of 173 households were surveyed, representing all households with children attending Rafiki Primary School who agreed to participate. The school belongs to a local NGO (Non-Governmental Organization), Kukorra Hamu Uganda, and is located in Kenziga village, Sembabule District. It is situated in a semi-rural setting and serves as a community hub for households from several surrounding villages, including, among others, Kenziga, Vvunza, Katwe, and Lwebusisi. Selecting households with children attending this school provided a practical and contextually grounded way to reach a diverse cross-section of rural families living in the area. This resulted in a non-probability convenience sampling approach [35], as participation was limited to households linked to the school network and willing to take part in the survey. While we acknowledge that this sampling frame may introduce a mild selection bias, since it excludes households without school-aged children, the strategy was considered suitable for the exploratory, community-based research, as it facilitated access to respondents across several nearby villages while ensuring feasibility and trust in data collection.

Data were collected on various household characteristics, including socioeconomic status, agricultural practices, and access to resources. Ethical approval for this research was obtained from both the Office for Responsible Research at the University Miguel Hernández de Elche [Reference: DEA.LMM.02.22] and from the local Ugandan partner institution, Kukorra Hamu Uganda, which holds authorization from the national regulatory authority [Reference: PDPO-202306-2193]. All procedures complied with the 1964 Helsinki Declaration and its later amendments. Informed consent was obtained from all participants prior to data collection. Respondents received an explanation of the objective of the study, emphasizing that it was entirely academic, that participation was voluntary, and that the information provided would be used exclusively for research purposes. They were assured that confidentiality was absolutely guaranteed and that their responses would have no bearing on their relationship with the NGO.

The study employed a two-part interview process. Data were collected through lengthy, structured interviews conducted jointly by the first author and a local social worker from Kukorra Hamu Uganda, who was fluent in both Luganda and English. In order to minimize potential social desirability bias arising from the involvement of the social worker, standardized prompts and confidentiality assurances were used, and it was ensured that she had no role in any project implementation. A specifically designed interview guide combined closed- and open-ended questions and was implemented through face-to-face interviews using the KoboToolbox platform (Computer-Assisted Personal Interviewing, CAPI). Before the main fieldwork, the questionnaire was reviewed for cultural and linguistic suitability and pretested with a small number of households from Katwe village to refine question wording; those households were not included in the final sample. To gather the necessary data, the research team travelled to each household to conduct the interviews, which lasted typically between 1.5 and 2 h and were conducted privately with the main respondent, to minimize external influence and ensure the confidentiality of responses. The initial set of interviews, conducted during February and March 2022, focused on gathering comprehensive information about the household members, including their education, health, and economic status. Additionally, the interviews included open-ended qualitative questions, providing respondents with a rare opportunity to share their problems and perceptions of their needs in an open and precise way—a practice that is often avoided in similar research due to the significant effort required to categorize and analyze such responses.

In the second phase of the study, carried out from September to October 2022, additional interviews were conducted to assess the food security status of the participating households. During these interviews, household members were asked about their agricultural practices, food sources, and other relevant factors used to calculate the food security scores through the proxy indicators, namely the FCS and the MAHFP. The indicators selected are straightforward to implement, extensively validated, supported by readily available data for comparison, and capable of capturing diverse aspects of food security to enhance and complement the research findings.

During the first wave of data collection (February–March 2022), 166 households were interviewed, while the second wave (September–October 2022) included 164 households. A total of 157 households participated in both waves, implying an attrition rate of 9 out of 166 households (5.4%), and 7 households were interviewed only during the second wave. In total, 173 unique households were surveyed across the study period. The FCS and MAHFP were collected exclusively during the second wave. Missing data were minimal and were handled by excluding incomplete responses from specific analyses, without removing entire households from the dataset.

The studied independent variables were either scaled or categorical in nature. Table 1 shows how the information was collected, resulting in 29 original independent variables. The selection of these variables was partly theory-driven, guided by prior studies on household food security determinants in sub-Saharan Africa (e.g., 32,34,36), which identified factors such as income, household size, land access, livestock ownership, and group membership as key predictors. Additionally, several variables were included in an exploratory manner to capture self-reported challenges and locally relevant household conditions.

Food security analysis

The calculation of the FCS and the MAHFP of each variable analysed has been carried out following the methodology proposed by the World Food Programme (WFP) and the Food and Nutrition Technical Assistance (FANTA) project, respectively.

On the one hand, the FCS is a composite metric used to assess household-level food security by measuring the

Table 1 Original independent variables studied

Variable	Type	Scale	Data format	Possible responses/Range	Ex-pect-ed effect
Distance to School	Quantitative	Ratio	Numeric	0 to infinite (whole numbers)	±
People living in the household	Quantitative	Ratio	Numeric	0 to infinite (whole numbers)	-
Main source of drinking water in the household	Qualitative	Nominal	Closed-Ended	Options: (1) Piped water, (2) Tube well or borehole, (3) Dug well, (4) Spring water, (5) Rain water, (6) Tanker truck, (7) Car with small tank, (8) Surface water (ponds), (9) Bottled water, (10) Other	+
Minutes walking for water	Quantitative	Ratio	Numeric	0 to infinite (whole numbers)	-
Method for making water drinkable	Qualitative	Nominal	Closed-Ended	Options: (1) Boil, (2) Ceramic filter, (3) Cloth filter, (4) Other	+
Toilet facility	Qualitative	Nominal	Closed-Ended	Options: (1) Pit latrine with slab, (2) Ventilated improved pit latrine, (3) Pit latrine without slab, (4) Open pit, (5) Hanging latrine, (6) Other	+
Share toilet facility	Qualitative	Nominal	Closed-Ended	Yes, No	-
Cooking fuel	Qualitative	Nominal	Closed-Ended	Options: (1) Electricity, (2) LPG, (3) Natural gas, (4) Biogas, (5) Kerosene, (6) Coal/lignite, (7) Charcoal, (8) Wood, (9) Straw/bushes/herbs, (10) Farm crops, 11. Manure, 12. No cooking at household, 13. Other	+
Household equipment	Qualitative	Nominal	Multiple-response	Options: (1) Electricity, (2) Radio, (3) Television	+
Household members asset ownership	Qualitative	Nominal	Multiple-response	Options: (1) Watch, (2) Phone, (3) Bicycle, (4) Motorbike	+
Water available for washing hands	Qualitative	Nominal	Closed-Ended	Yes, No	+
Soap available for washing hands	Qualitative	Nominal	Closed-Ended	Yes, No	+
House floor type	Qualitative	Nominal	Closed-Ended	Options: (1) Cement, (2) Dirt, (3) Tile, (4) Other	+
House roof type	Qualitative	Nominal	Closed-Ended	Options: (1) Natural roof, (2) Constructed roof	+
Minimum Necessary Household Income	Quantitative	Ratio	Numeric	Any non-negative number (e.g., 0, 100, 5000)	-
Real income	Quantitative	Ratio	Numeric	Any non-negative number (e.g., 0, 100, 5000)	+
Mentioned problems	Qualitative	Nominal	Open-ended	Free-text responses (paragraphs)	-
Land tenure	Qualitative	Nominal	Closed-Ended	(1) Own property, (2) Rented property	+
Size of farmland	Qualitative	Ordinal	Closed-Ended	1: Less than 1 acre, 2: Exactly 1 acre, 3: Bigger than 1 acre	+
Crops grown	Qualitative	Nominal	Open-ended	Any crop name (e.g., maize, beans, cassava)	+
Yield satisfaction	Qualitative	Nominal	Closed-Ended	Yes, No	+
Farming obstacles	Qualitative	Nominal	Open-ended	Free-text responses (paragraphs)	-
Home garden	Qualitative	Nominal	Closed-Ended	Yes, No	+
Livestock ownership	Qualitative	Nominal	Closed-Ended	Yes, No	+
Livestock type	Qualitative	Nominal	Open-ended	Any animal name (e.g., sheep, chickens, pigs)	±
Selling of agricultural surplus	Qualitative	Nominal	Closed-Ended	Yes, No	+
Farmers group membership	Qualitative	Nominal	Closed-Ended	Yes, No	+
Food source	Qualitative	Nominal	Closed-Ended	Options: (1) We buy at shop/market, (2) We grow it ourselves, (3) Work for food, (4) People help the family	+

"+" indicates an expected positive association with household food security, "–" a negative association, and "±" an ambiguous or context-dependent relationship. Expected directions were derived from previous empirical studies and theoretical reasoning when evidence was limited

diversity and frequency of food groups consumed over a seven-day recall period. As described by the World Food Programme [29], foods are categorized into groups, with each group assigned a weight based on its relative nutritional value. The FCS is calculated by multiplying the number of days of consumption of each food group (F_i) by its assigned weight (W_i) and then summing the values to produce a total score [36], as is shown in Eq. (1). Following WFP guidelines, the eight food groups and their corresponding weights were: meat, fish and eggs (4), dairy (4), pulses (3), staples (2), vegetables (1), fruits (1), oil/fat (0.5), sugar (0.5) and condiments (0). Consumption frequencies exceeding seven days were capped to 7 to maintain comparability across households. The resulting score provides insights into both the quality and quantity of a household's diet, with higher numbers reflecting better food consumption. It serves as a key indicator for identifying households with inadequate diets and monitoring broader food security trends within a population [37, 38].

$$FCS = \sum_{i=1}^{n} (F_i x W_i) \quad (1)$$

Where:

- F_i = Number of days a particular food group i was consumed over a seven-day recall period.
- W_i = Weighting factor assigned to each food group based on its nutritional value.
- n = Total number of food groups considered (in this case, 8 food groups).

On the other hand, the MAHFP measures household food security by tracking the number of months in the past year during which a household was able to meet its food requirements. The calculation, explained by Bilinsky & Swindale [30], involves recording the number of months when a household did not experience food shortages and summing them to determine the total adequate months. This indicator provides insights into temporal trends in food security, highlighting periods of vulnerability and identifying patterns of seasonal or chronic food shortages. The standard FANTA [30] question —"In which months did your household not have enough food to meet its needs?"— was used without modification, translated into Luganda to ensure comprehension. Each respondent was asked to report conditions for all twelve months of the previous year, allowing for full comparability with the standard MAHFP methodology. A higher number of adequate months indicates greater food security, reflecting a household's sustained access to food throughout the year. Widely adopted and validated —used, for example, in rural Kenya [15] and among farming households in Zambia [39]— the MAHFP complements other indicators like the FCS, allowing for comparability across studies and contexts. Its computation is summarized in Eq. (2), where the total number of adequate months is obtained by subtracting the number of shortage months from the twelve months of the reference period:

$$MAHFP = 12 - \sum_{i=1}^{12} M_i \quad (2)$$

Where:

- M_i = Binary value for month , where:
  - $M_i = 1$ if the household experienced food shortage during month .
  - $M_i = 0$ if the household did not experience food shortage during month .

The collected data were analysed using SPSS v26.0. To ensure meaningful variability among predictors, variables were excluded when their responses were highly polarized—defined as having 85% or more of respondents selecting the same category. This rule was applied to avoid including predictor variables with insufficient variation to distinguish between food-secure and food-insecure households. The 85% threshold, although not derived from a specific prior study, was chosen pragmatically to balance parsimony and information retention, ensuring that only variables providing adequate differentiation across households were retained for analysis.

Missing data were handled using a pairwise deletion approach, excluding incomplete observations only from the specific analyses in which they appeared, while retaining all households in the dataset. This method was considered appropriate given the limited proportion of missing responses and the exploratory nature of the study. Continuous predictors were kept in their original units rather than standardized to preserve interpretability of the coefficients and facilitate direct comparison with similar studies. Categorical variables comprising more than two categories were transformed into "dummy" variables (1: presence/0: absence).

The distributions of the independent variables were then examined in relation to the FCS and MAHFP results. FCS range extended from 0 to 112, with higher scores indicating better food security. MAHFP ranged from 0 to 12 months, with a higher number of adequate months also reflecting greater food security. The Shapiro–Wilk test was applied to the outcome variables (FCS and MAHFP) within each group of the categorical predictors to verify the assumption of normality prior to conducting ANOVA tests. Homogeneity of variances was examined using Levene's test. All statistical tests were two-tailed and conducted at a 5% significance level ($\alpha = 0.05$).

Subsequently, the population was divided into two groups -"food secure" and "food insecure"- based on the indicators used. Notably, the use of the two different food security indicators resulted in two distinct classifications of the population. For the FCS indicator, the official thresholds were used to create these two categories. In accordance with WFP guidelines [29], households classified as "poor" (scores 0 to 21) or "borderline" (scores 21.5 to 35) were grouped together and considered food insecure. Households with scores above 35, categorized as "acceptable," were deemed food secure. This grouping was statistically assessed through an additional comparison using the original three FCS categories. The analysis showed that the "poor" and "borderline" groups shared comparable socioeconomic profiles and livelihood patterns, clearly distinct from the "acceptable" category. Therefore, merging the two lower categories was both methodologically consistent with previous studies [19, 34] and statistically justified, while facilitating binary logistic regression modeling.

Regarding the MAHFP indicator, since there are no categorical thresholds established in the official technical guidelines [30], the thresholds used in prior studies were employed to ensure comparability. In this framework, authors like Matavel et al. [32] have considered individuals with a score of 5 months or less as the most food insecure (category 1), those with 6 to 9 months as moderately food insecure (category 2), and those with 10 months or more as the least food insecure (category 3). In the present study, categories 1 and 2 as defined by Matavel et al. [32] were merged and designated as "food insecure", representing households with a MAHFP score of 9 months or less. Category 3 (scores of 10 months or more) was classified as "food secure". To verify the robustness of this classification, a sensitivity analysis was conducted using alternative cut-offs (≤ 8 vs. ≥ 9 and ≤ 10 vs. ≥ 11 months). Cohen's κ was calculated to assess the agreement between MAHFP and FCS-based classifications. Although the ≤ 8 vs. ≥ 9 threshold produced a slightly higher κ value (0.37), the ≤ 9 vs. ≥ 10 cut-off was retained, as it is conceptually consistent with previous literature.

A contingency table analysis and one way ANOVA (Analysis of Variance) test were conducted to systematically organize and analyze the categorical and continuous data, respectively. This approach used the dichotomous food security classification (derived from the FCS and MAHFP indicators) as the grouping factor to compare mean differences in the quantitative independent variables across the groups. These preliminary analyses served two main purposes: first, to select candidate variables for the logistic regression models, and second, to compare the relative capacity of the two indicators (FCS and MAHFP) to discriminate between food-secure and food-insecure households. While we acknowledge that continuous socioeconomic variables may not always strictly satisfy the assumption of normality, these tests were employed here as an exploratory screening tool to identify which independent variables showed significant unadjusted associations with food security status before selecting them for the final regression models.

Additionally, bivariate correlations were examined to assess the strength and direction of the dependent variables and the food security indicators, to prevent potential multicollinearity issues.

The final selection of predictors was based on both their theoretical relevance and statistical significance. Pairwise correlations were examined to minimize collinearity, and no variables showing strong associations were included together in the same model. Therefore, the final regressions retained a parsimonious set of conceptually meaningful predictors, balancing empirical evidence and theoretical justification.

Logistic regression analysis

A binary logistic regression model was determined as the most appropriate method to further explore the factors influencing food security, due to its suitability for dichotomous dependent variables, allowing the classification of households as "food secure" or "food insecure". This approach estimates the probability of food security outcomes based on independent variables without assuming linear relationships, utilizing the logit transformation to accommodate non-linear patterns typical in socioeconomic data. It provides interpretable odds ratios, offering clear insight into the effects of predictor variables, and supports both categorical and scaled predictors for comprehensive analysis. This method has also been effectively applied in similar contexts, such as in Northern Ethiopia to identify key household food security determinants [40], reinforcing its relevance for generating actionable insights for policymakers and stakeholders aiming to improve food security outcomes.

The logistic regression model estimates the probability that a given household is food secure. This probability, p_i, is expressed by the Eq. (3).

$$p_i = \frac{e^{\beta_0+\beta_1X_1+\beta_2X_2+\ldots+\beta_kX_k}}{1+e^{\beta_0+\beta_1X_1+\beta_2X_2+\ldots+\beta_kX_k}} \tag{3}$$

Where:

- p_i = Probability that the -th household is food secure (=1).
- β_0 = Intercept or constant term.
- β_j = Coefficient associated with the j-th predictor variable X_j (for j = 1, 2…, k).
- X_j = Independent variables representing potential determinants of food security.

The model can be rewritten in its logit form as is shown in Eq. (4).

$$Logit\,(p_i) = lnln\left(\frac{p_i}{1-p_i}\right) = \beta_0+\beta_1X_1+\beta_2X_2+\ldots+\beta_kX_k \tag{4}$$

In this form, the dependent variable is the natural logarithm of the odds ratio of being food secure versus being food insecure.

The coefficients (β_j) represent the change in the log-odds of food security status associated with a one-unit change in the predictor variable, holding all other variables constant.

The odds ratio (OR) is calculated by exponentiating the coefficient as is shown in Eq. (5).

$$OR = e^{\beta_j} \tag{5}$$

Where:

- OR > 1: The predictor variable increases the probability of being food secure.
- OR < 1: The predictor variable decreases the probability of being food secure.
- OR = 1: The predictor variable has no effect on food security status.

The statistical significance of each predictor is assessed using the Wald test, with p-values less than 0.05 considered statistically significant.

To evaluate the performance of the logistic regression model, various measures were considered:

- Hosmer-Lemeshow Test: Assesses the calibration of the model, indicating how closely predicted probabilities match observed probabilities. A p-value > 0.05 suggests good fit.
- Nagelkerke R^2: Indicates the proportion of variation in the dependent variable explained by the model.
- Classification Table: Compares observed and predicted classifications to calculate the overall percentage of correct classifications.
- Area Under the ROC Curve (AUC/ROC): Evaluates the discriminatory capacity of the model, quantifying its ability to correctly distinguish between food-secure and food-insecure households.
- Brier Score and Calibration Plot: The Brier score was computed to assess the accuracy of predicted probabilities, while calibration plots were inspected to verify the correspondence between predicted and observed probabilities.
- Classification Threshold and Internal Validation: A probability threshold of 0.5 was used to classify households as food secure or food insecure. Internal validation was conducted through repeated random subsampling to test the models' stability and robustness.

Two separate binary logistic regression models were estimated—one using the FCS-based classification and another using the MAHFP-based classification—to capture the distinct temporal dimensions represented by each indicator. Given the cross-sectional nature of the data, the models identify statistical associations rather than causal relationships, as data were collected at a single point in time.

Post-estimation diagnostics were conducted to ensure the validity of the logistic regression models. Multicollinearity was assessed using the Variance Inflation Factor (VIF), with a threshold of VIF < 2.5 indicating acceptable levels. The assumption of linearity of the logit for the continuous variable ("Minimum Necessary Household Income") was verified using the Box-Tidwell test (interaction with its natural logarithm), which yielded non-significant results ($p > 0.05$). Finally, influential cases were screened using Cook's Distance, identifying no observations with values exceeding the critical threshold of 1.0.

Results and discussion

General food security classification

Participating households were distributed across 19 different villages or hamlets, with nearly half (43.9%) originating from Kenziga village, where the primary school established by the local NGO is located. When asked whom they considered the most suitable person to participate in the interview, women emerged as the primary respondents in most cases (98.2%). This outcome may reflect prevailing gender roles in rural Uganda, where women are primarily responsible for food preparation, resource management, and child care, and therefore possess the most accurate knowledge of household food consumption and food access. This gender pattern also presents a clear policy opportunity, in that prioritising women through tailored extension services could enhance the effectiveness of food security interventions. Water availability was largely dependent on the surface ponds or waterholes present in the area. In this regard, 90.8% of the surveyed households reported collecting household water from these ponds, with an average daily collection time of 70 min. To contextualize this finding, national statistics from the Uganda Bureau of Statistics (UBOS) indicate that most agricultural households rely on protected water sources such as public boreholes (38%), protected wells or springs (15%), or public taps (12%), while only 13% use unprotected wells or springs as their main source of drinking water [41]. This places the study area among the most water-deprived rural settings in the country. Time-saving interventions such as the installation of protected water points, communal storage drums, or household-level handwashing stations would therefore substantially reduce the daily labour burden. The minutes of water-collection time saved could be incorporated as a measurable KPI in future program evaluations, given its relevance for labour allocation, childcare, and income-generating activities. To purify the water, 93.6% of respondents reported boiling as their primary method. Additionally, 85% of households reported having access to land for cultivation or raising animals;

Table 2 Food security classification of interviewed households

	Food Secure	95% CI	Food Insecure	95% CI	Mean Score (95% CI)	SD
FCS	58.54% (*n* = 96)	51.0–66.0%	41.46% (*n* = 68)	34.0–49.0%	42.02 (39.0–45.0)	19.33
MAHFP	31.10% (*n* = 51)	24.0–38.1.0.1%	68.90% (*n* = 113)	61.8–76.0%	7.23 (6.74–7.71)	3.17

FCS: Food insecure = FCS ≤35; Food secure = FCS >35. MAHFP: Food insecure = MAHFP ≤9 months; Food secure = MAHFP ≥10 months

Table 3 Cross-tabulation of household food security status based on FCS and MAHFP

	MAHFP insecure	MAHFP secure	Total FCS
FCS Insecure	56	12	68
FCS Secure	57	39	96
Total MAHFP	113	51	164
Agreement (κ)	Cohen's κ = 0.214 (95% CI: 0.085–0.335)		

Households classified as FCS-secure but MAHFP-insecure may require resilience-oriented support (e.g., post-harvest loss reduction). Households classified as FCS-insecure but MAHFP-secure may benefit from short-term consumption or access-related assistance. Households insecure under both indicators represent the highest-priority group for comprehensive support, whereas households secure under both indicators constitute a lower-priority group

however, more than one-third (36.5%) of them own 0.5 acres or less.

The interviewed households were classified as either food secure or food insecure, based on their scores on the two food security indicators used. This resulted in two distinct classifications of the population (Table 2).

Although the mean FCS exceeds the threshold of 35—placing the sample within the "acceptable" range—a substantial proportion of households (41.46%) are still classified as food insecure. This figure increases markedly when using the MAHFP indicator: according to this metric, more than two-thirds (68.9%) of households are food insecure, despite reporting an average of over seven months of adequate food provisioning. This difference clearly reflects the fact that the two indicators capture different dimensions of food security, a pattern also observed in other African contexts—for example, Matavel et al. [32] found that FCS tends to reflect short-term, purchase-driven consumption while MAHFP captures year-round adequacy and farm-sourced provisioning, leading to similarly divergent classifications of households. In our sample, the formal agreement between both indicators was only fair (Cohen's κ = 0.21), reinforcing the conclusion that each metric identifies a distinct subset of vulnerable households.

Comparison between FCS and MAHFP classifications

A cross-tabulation was conducted to assess the degree of agreement between household classifications derived from the two food security indicators used in this study: FCS and MAHFP. As shown in Table 3, the two indicators produced divergent classifications for a substantial proportion of households. Beyond measuring agreement, this cross-classification also serves a programmatic purpose: combining both indicators allows implementers to stratify households into complementary vulnerability profiles, distinguishing those requiring short-term consumption support from those needing resilience-oriented or seasonal interventions.

Out of the 164 households included in the food security analysis, only 95 (57.9%) were consistently classified as either food secure or food insecure by both indicators. The remaining 69 households (42.1%) were categorized differently depending on the metric used. Specifically, 57 households were considered food secure by the FCS but food insecure by the MAHFP, representing a potential pilot cohort for resilience-oriented interventions such as improved household or community granaries, post-harvest loss reduction measures, or Village Saving and Loan Associations (VSLAs) aligned with the lean season. Conversely, 12 households showed the opposite pattern—MAHFP-secure but FCS-insecure. These could benefit more from short-term access or diet-quality interventions, including nutrition counselling or improved market access for diverse foods.

These discrepancies reflect the fact that the two indicators capture different dimensions of food access. The FCS assesses recent food consumption patterns over the past seven days and is therefore sensitive to short-term shocks, market access, and temporary changes in diet quality or diversity around the moment of data collection. In contrast, the MAHFP summarizes a household's capacity to secure adequate food across the entire agricultural year, signalling longer-term seasonal resilience or chronic deficits in production, storage, and income smoothing. As noted by Mutea et al. [15], food security assessments based on multiple complementary indicators provide a more reliable and nuanced understanding of household conditions, especially in contexts marked by seasonal fluctuations, and they also help translate results into clear programmatic actions. In this sense, households identified as insecure by the FCS are more likely to benefit from short-term consumption, whereas those classified as insecure by the MAHFP may require resilience-oriented support.

The timing of the assessment plays a crucial role not only in shaping the results but also in how they are interpreted. The interviews used to calculate both indicators took place between September and October 2022, shortly after the harvest season in central Uganda. This period typically coincides with improved food availability, due to the "harvest effect", whereby households temporarily experience better dietary intake as newly harvested foods enter the home. However, the 2022 agricultural season was severely affected by drought, which reduced yields across the country. According to the World Meteorological Organization [42], both the March–May and October–December rainy seasons recorded below-average precipitation, contributing to the most prolonged drought in over four decades. Even so, the timing of data collection—immediately after harvest—may have softened the impact of the drought on short-term food consumption. As a result, households might have had some food stored, which could explain the relatively better FCS scores. In contrast, the MAHFP, based on a 12-month recall, captured the cumulative effects of food shortages experienced throughout the year, classifying a greater proportion of households as food insecure. This seasonal dynamic has also been observed in other parts of East Africa. In Kenya, Mutea et al. [15] show that short-term food security indicators—such as dietary diversity or consumption-based metrics—tend to classify most households as food secure, while longer-recall indicators such as the MAHFP capture substantially higher levels of food insecurity, reflecting deficits accumulated throughout the year. A study conducted in central Mozambique found that food security levels peaked during the post-harvest period (May–July), followed by the harvesting season, and were lowest during the lean period (November–January) [32]. In line with this seasonal dynamic, repeating the FCS during the lean season and collecting MAHFP on an annual basis would provide a more complete picture of household vulnerability. A practical monitoring metric could be the proportion of households maintaining an "acceptable" FCS threshold during the lean months, which would help track progress in seasonal resilience.

These results highlight the value of using multiple complementary indicators in food security assessments, and are consistent with well-established recommendations in the literature. Authors like Maxwell et al. and Mutea et al. [15, 18] argue that relying on a single metric risks misclassifying households and either under or overestimating the severity of food insecurity, particularly in highly seasonal contexts.

Household and livelihood differences across food security groups

Regarding the predictors, a total of 21 variables were retained for the analysis after the exclusion of polarized variables. When disaggregated by food security status, the households were classified as presented in Tables 4, 5 and 6. For categorical variables, differences between food-secure and food-insecure households were tested using chi-square tests; for continuous variables, ANOVA was used.

Tables 4 and 5 present cross-tabulations showing the distribution of households across food security groups based on each qualitative variable, classified according to the two indicators employed: FCS and MAHFP. Specifically, Table 4 highlights household characteristics and livelihood practices, while Table 5 focuses on reported challenges and constraints faced by each household. Table 6 provides a comparative analysis of quantitative variables by reporting the mean values for each food security group under both classification systems. The variables identified as statistically significant in each indicator effectively distinguish between food-secure and food-insecure households. While some variables exhibit significance across both indicators, others are only significant under one classification criterion. It is worth noting that the FCS classification detected a higher number of significant variables compared to the MAHFP, reflecting differences in how each indicator captures various dimensions of food security. However, some key predictors were statistically significant across both indicators. Consistent differences emerged in sanitation conditions, basic household assets, and agricultural capacity—particularly farmland availability and the ability to sell surplus. Reports of deprivation (hunger, lack of clothing) and perceived minimum income requirements also distinguished food-secure from food-insecure households. For significant predictors, program levers and referral pathways were developed to indicate suggestions from a programmatic perspective.

For operational interpretation, indicative minimum thresholds can be derived for the quantitative variables with the greatest programmatic relevance. Households reporting a minimum necessary income at least 10,000 UGX/week above their real income may be prioritised for case management or financial-literacy support; water-collection times exceeding 60 min per day may indicate the need for WASH (Water, Sanitation and Hygiene) upgrades or time-saving interventions. These indicative minimum thresholds are not statistical cut-offs, but practical reference points intended to help implementers stratify households according to likely intervention needs.

General household characteristics

Food-secure households generally exhibited better overall conditions across the measured variables. The link between food security and hygiene and sanitation is evident in the significant differences observed in toilet facility sharing, particularly under the FCS classification. Specifically, the majority of food-insecure households (51.6%) shared toilet facilities, compared to only 34% of food-secure households, highlighting a disparity in access to private sanitation. Moreover, differences in sanitation extended beyond toilet facility sharing,

Table 4 Households distribution (%) by food security Group, household characteristics and livelihood practices (FCS & MAHFP)

Variable	FCS				MAHFP			Program lever
	Mean n = 157	Insecure households n = 64	Secure house-holds n = 93	Sig.	Insecure house-holds n = 107	Secure house-holds n = 50	Sig.	
Type of Toilet Facility								
Pit latrine with slab	83.4	85.9	81.7	ns	82.2	86.0	ns	
Ventilated improved pit latrine	8.9	4.7	11.8	ns	8.4	10.0	ns	
Pit latrine without slab	5.7	6.3	5.4	ns	7.5	2.0	ns	
Open pit	5.7	6.3	5.4	ns	7.5	2.0	ns	
Share toilet facility	41.7	51.6	34.8	**	45.3	34.0	ns	Construction/rehabilitation of household latrines
Water available for washing hands	80.3	68.8	88.2	**	76.6	88.0	*	Installation of handwashing points near homes/latrines
Soap available for washing hands	79.6	68.8	87.1	**	76.6	86.0	ns	Subsidized hygiene kits
Household equipment								
Electricity	68.2	57.8	75.3	**	66.4	72.0	ns	Distribution of solar-home systems
Radio	38.9	29.7	45.2	*	32.7	52.0	**	Radio-based education
T.V.	21.0	10.9	28.0	**	16.8	30.0	*	Community viewing points
Bicycle	30.6	26.6	33.3	ns	29.0	34.0	ns	
Motorbike	15.3	7.8	20.4	**	12.1	22.0	ns	Mobility support
House floor type (Cemented)	47.8	31.3	59.1	**	43.9	56.0	ns	Floor improvement
Size of farmland (more than 0.5 acres)	63.5	50.8	72.3	**	59.6	72.0	ns	Access-to-land programs
Crops grown								Subsidized input packages, agricultural extension programs
Maize farming	78.7	69.1	85.4	**	77.0	82.4	ns	
Coffee farming	26.8	19.1	32.3	*	21.2	39.2	**	
Plantain farming	24.4	17.6	29.2	*	18.6	37.3	**	
Home garden	17.7	20.6	15.6	ns	17.7	17.6	ns	
Livestock ownership	65.9	58.8	70.8	ns	62.8	72.5	ns	
Livestock type								
Chickens	18.9	13.2	22.9	ns	19.5	17.6	ns	
Goats	23.2	14.7	29.2	**	19.5	31.4	*	Subsidized livestock packages
Pigs	39.0	41.2	37.5	ns	38.9	39.2	ns	
Selling of agricultural surplus	50.6	36.8	60.4	**	46.0	60.8	*	Market linkage
Food source								
Shop/market	73.8	73.5	74.0	ns	73.5	74.5	ns	
Home grown	68.9	57.4	77.1	**	66.4	74.5	ns	Home-garden starter kits
Work for food	7.9	14.7	3.1	**	10.6	2.0	*	Public work programs
People help the family	1.2	1.5	1.0	ns	0.9	2.0	ns	

* $p < 0.1$, ** $p < 0.05$. Variables in bold represent key actionable levers for intervention

with food-secure households exhibiting greater access to essential hygiene resources, particularly under the FCS indicator. Specifically, 88.2% of food-secure households, according to the FCS, reported access to water for washing hands, compared to only 68.8% of food-insecure households. According to the MAHFP the trend was similar, with 88% of food-secure households having access, compared to 76.6% of food-insecure households. The availability of soap also emerged as a distinguishing factor under the FCS classification, being, again, more prevalent among food-secure households. These findings align with Workman et al. [43], who emphasize the complex, multi-dimensional nature of food, water, and sanitation insecurities, highlighting how these issues frequently coexist and interact, resulting in notable impacts on both mental and physical health. In Uganda, Musoke et al. [44] show that inadequate sanitation, shared latrines, and limited access to safe water in low-income communities contribute to recurrent diarrhoeal disease and malnutrition, two pathways widely recognised as undermining household food security in resource-limited settings. Similarly, in Ethiopia, Lee et al. (2022) report that poor

Table 5 Households distribution (%) by food security Group, reported challenges and constraints (FCS & MAHFP)

Variable	FCS				MAHFP			Referral pathway
	Mean $n=157$	Insecure households $n=64$	Secure households $n=93$	Sig.	Insecure households $n=107$	Secure households $n=50$	Sig.	
General problems								
Poverty, money	61.8	64.1	60.2	ns	57.0	72.0	*	Linkages to livelihood/VSLA support
Hunger, lack of food	38.9	53.1	29.0	**	43.9	28.0	*	Food voucher/CBT inclusion
School fees	33.1	34.4	32.3	ns	31.8	36.0	ns	
Lack of clothes	35.7	51.6	24.7	**	40.2	26.0	*	Linkages with social protection
Lack of mattress or bedding	22.9	34.4	15.1	**	26.2	16.0	ns	Linkages with social protection
Disease or lack of access to medical treatment	64.3	60.9	66.7	ns	63.6	66.0	ns	
Access to drinking water	20.4	10.9	26.9	**	14.0	34.0	**	WASH upgrades; KPI = time-to-source
Insufficient farmland	15.3	21.9	10.8	*	19.6	6.0	**	Access-to-land programs
Farming obstacles								
Lack of rain water	83.5	77.9	87.5	ns	80.5	90.2	ns	
Soil is not fertile	75.0	80.9	70.8	ns	77.0	70.6	ns	
Land access	15.2	14.7	15.5	ns	14.2	17.6	ns	
Land size	49.4	55.9	44.8	ns	52.2	43.1	ns	

* $p<0.1$, ** $p<0.05$

sanitation and limited handwashing practices are associated with both greater food insecurity and higher rates of child malnutrition.

Food-secure households were generally better equipped than their food-insecure counterparts in terms of access to electricity and higher-quality flooring. In settings like rural Uganda, where cash income is often irregular or difficult to measure, such basic household assets could function as practical wealth proxies, offering a more stable picture of living standards than self-reported income. In fact, indicators such as night-time lights are increasingly employed by social scientists as proxies for local economic activity and development, particularly in settings where up-to-date statistics are limited or unavailable [45]. Our results are consistent with those by Frayne & McCordic [46], who demonstrated that households with inconsistent or no access to a cash income, electricity, or water among others, had 8.5 times greater odds of having less than 12 months of adequate food provisioning in the last year. These differences were even more pronounced under the FCS classification compared to the MAHFP classification. Apanovich & Mazur [47] also identified access to electricity as a socioeconomic indicator in their study of food security among smallholder farmers in Uganda, although its direct effect on food security was not statistically significant in the final analysis. Similarly, ownership of assets such as televisions, radios, and motorcycles followed the same trend. This aligns with the findings of Shifat et al. [48], who identified a strong positive association between household asset ownership and food security in Bangladesh. Their study suggests that the absence of such assets signals economic vulnerability and may serve as a practical proxy indicator in contexts where detailed income or consumption data are lacking. Given this, asset-based targeting may be particularly useful for implementers when income data are unreliable or incomplete. In such contexts, implementers may also consider piloting solar-kit microfinance models—already tested in different countries of East Africa [49]—as a way to strengthen basic household assets and improve welfare among low-income households.

With respect to the quantitative variables (Table 6), household size and those related to income emerged as significant factors in food security, particularly under the FCS classification. The literature generally suggests that larger household sizes contribute to greater food insecurity due to increased consumption demands relative to production or income capacity [19, 50, 51]. However, contrary to this widely held view, our findings indicate that larger households (with an average of 7.89 members) were more likely to be classified as food-secure using the FCS indicator, compared to smaller households (6.73 members), in line with findings by Nkomoki et al. [34] and Maitra and Rao [52], who also observed a positive association between household size and food security in specific rural contexts. In East African contexts, recent studies by Jisso et al. [53] and Wubetie et al. [54] in Ethiopia found that larger households were less likely to fall

Table 6 Comparative analysis of quantitative variables by food security status (FCS and MAHFP, ANOVA Results)

Variable	Total		FCS						MAHFP					
			Insecure households		Secure households				Insecure households		Secure households			
	Mean	SD	Mean	SD	Mean	SD	Sig.	Cohen's d	Mean	SD	Mean	SD	Sig.	Cohen's d
Walking time to school (minutes)	72.52	47.99	75.11	54.45	70.73	43.21	ns	0.09	71.07	47.92	75.60	48.47	ns	−0.09
Household size (members)	7.42	3.24	6.73	2.29	7.89	3.69	**	−0.36	7.23	2.78	7.82	4.04	ns	−0.18
Water collection time (minutes/day)	70.15	35.68	71.95	36.62	68.89	35.16	ns	0.09	68.52	33.45	73.58	40.11	ns	−0.14
Minimum necessary household income (UGX/Week)	25,531	24,549	18,004	12,729	30,659	29,023	**	−0.53	23,19	21,859	30,646	29,201	*	−0.31
Real income (UGX/Week)	16,477	31,754	9,372	14,873	21,317	38,659	**	−0.38	14,08	23,770	21,716	44,381	ns	−0.24

* $p < 0.1$, ** $p < 0.05$. Positive values of Cohen's d indicate higher means among food-insecure households; negative values indicate higher means among food-secure households

into higher food insecurity categories, due to increased availability of household labour for subsistence production and off-farm income.

A number of mechanisms may account for this counterintuitive relationship. Larger households may benefit from labour-sharing dynamics, whereby more working-age members contribute to cultivation, food preparation, water collection, childcare, or small income-generating activities—effectively easing the labour constraints that typically limit production in rural households. In addition, extended family arrangements may serve as informal safety nets, enhancing household resilience through pooled labour, reciprocal food transfers, and diversified livelihood strategies. In this sense, household size may not function as a simple consumption burden, but rather as a flexible resource that enhances food access and stability across seasons.

The mean income reported by our sample was 16,477 UGX per week, a level broadly consistent with the lower end of rural income distributions in Uganda. For comparison, UBOS report from the 2023/2024 National Household Survey [55] states median monthly earnings of 120,000 UGX among rural workers—equivalent to roughly 28,000 UGX per week—placing our sample well within the income range typical of low-income rural households. Furthermore, the income reported by each group was higher among food-secure households, although the difference was statistically significant only under the FCS classification (21,317 UGX/week vs. 9,372 UGX/week). This finding is consistent with the broader literature, which establishes a strong link between household income and food security. For example, Tulem & Hordofa [56] reported that households with a low wealth index were over four times more likely to be food insecure compared to wealthier households. Similarly, a study by Kundu et al. [57] reported that higher household wealth status was significantly associated with greater minimum dietary diversity among children aged 6–23 months in Bangladesh, highlighting the influence of socioeconomic factors on dietary quality. Furthermore, the Minimum Necessary Household Income suggests that food-secure households required substantially more income to cover basic household needs—70.29% higher than food-insecure households under the FCS indicator and 32.13% higher under the MAHFP indicator. This may reflect higher living standards among food-secure households, where greater financial resources are required to maintain improved housing, better diets, and access to essential services. Additionally, food-secure households may have more complex financial commitments, including school fees, healthcare costs, and investments in agricultural inputs, which elevate their minimum income requirements. From a programmatic perspective, these discrepancies between reported income and 'minimum necessary income' point to potential gaps in household financial planning. Interventions such as basic budget-coaching, cash-flow mapping, or envelope-budgeting approaches—often delivered through VSLAs—may help households align their expenditures with monthly cash availability and reduce vulnerability to short-term food shortages. In practical terms, households reporting a minimum necessary income at least 10,000 UGX per week above their stated income could be prioritised for case management or targeted financial-literacy support.

Regarding walking time to school and water collection time, these variables showed no statistical significance with FCS and MAHFP.

Land ownership and agricultural practices

Farmland size is widely recognized as a key determinant of household food security [20, 34, 47, 58, 59] and our findings support this association. In our case, farmland size was significantly linked to food security when applying the FCS classification, with 72.3% of food-secure households owning larger land areas compared to only 50.8% of food-insecure households (see Table 4). This result aligns with the findings of Apanovich and Mazur [47], who reported a positive relationship between total acreage and food security among Ugandan smallholder farmers during both the harvest and lean seasons. Similarly, Nkomoki et al. [34] observed that larger farm sizes increased the likelihood of household food security, explaining that greater land access allows households to produce more food for self-consumption (enhancing food availability), diversify crops (improving dietary diversity and resilience), and sell surplus produce (increasing economic access to food). Our results further support this interpretation (Table 4): food-secure households were more likely to cultivate crops such as maize, coffee, and plantains, and to engage in livestock rearing, all of which contribute to improved food availability and income generation. Moreover, the sale of agricultural surplus was more prevalent among food-secure households and was significantly associated with food security status under both FCS and MAHFP classifications. Similar findings were reported by Mengistu et al. [60] in Ethiopia, where crop diversification significantly improved household food security by enhancing dietary diversity, stabilizing income sources, and mitigating production risks among smallholder farmers. In contrast, food-insecure households often consumed most of their produce, leaving little or no surplus for sale, thereby limiting their capacity to earn income from farming.

Beyond household-level differences in farmland size and crop diversity, these findings also resonate with Uganda's ongoing land-tenure reforms. Recent national policies have emphasised strengthening security of tenure—particularly under customary systems—to reduce land fragmentation, protect smallholder rights, and expand cultivable acreage for rural households. In practice, more secure tenure has been shown to encourage longer-term investments in soil fertility, perennial crops such as coffee or banana/plantain, and small-scale livestock, all of which are strongly aligned with the food-secure profiles observed in our sample.

From an implementation standpoint, the combination of crop data and reported land constraints points to opportunities for tiered input packages tailored to different household land sizes. Households with less than 0.5 acres could benefit from low-space, high-return kits (e.g., maize–beans mini-bundles, home-garden starter kits), whereas those with 0.5–1 acre might be supported through maize–plantain packages or small ruminants. Households with more than 1 acre—and who already sell some surplus—would be well suited for coffee starter kits, plantain–coffee intercrop packages, or market-access support such as bulking, collective marketing, or transport facilitation. Linking such tiered packages to evolving land-tenure reforms could help ensure that increases in land access translate into tangible improvements in production, crop diversification, and market integration.

When asked about their primary food sources, two variables showed significant differences across the population: growing food at home and working for food as payment—a common practice in rural Uganda where labour is exchanged for food instead of monetary compensation. Growing food at home was more prevalent among food-secure households, likely due to their access to larger plots of land compared to food-insecure households. This finding aligns with the results of Issahaku et al. [61], who reported a 4.6% increase in Food Consumption Scores (FCS) among Rwandan households practicing home gardening, reflecting improved dietary diversity and overall food security. Given this pattern, households relying on home-grown food—typically those with slightly larger plots—would benefit from support aimed at expanding small-scale production capacity. Simple kitchen-garden models and low-cost drip-irrigation kits could help lower-land households increase year-round vegetable availability, reduce dependence on purchased foods, and strengthen dietary diversity, even under drought-prone conditions. In contrast, although not a widespread strategy—reported by only 7.9% of surveyed households—working for food was more frequently observed among food-insecure households, possibly indicating their urgent need to secure sustenance for their household. Programmatically, this points to the value of developing cash-for-work alternatives—with clear safeguards regarding payment reliability—and establishing transparent parity between food wages and equivalent cash wages, to avoid undervaluation of labour. To our knowledge, no empirical studies have examined how food-for-labour arrangements relate to household food security in Uganda or the wider East African region. This absence of evidence highlights a clear research gap, and consequently no direct comparisons with previous findings could be established.

Challenges reported

Open-ended responses revealed that food-insecure households reported a higher prevalence of various issues, such as hunger and lack of clothing, than their food-secure counterparts under both indicators (Table 5). These issues can be considered direct indicators of poverty, a condition strongly correlated with food insecurity across various countries [62]. Limited financial resources among food-insecure households often force them to prioritize immediate food needs over other essentials, further perpetuating cycles of deprivation. Similarly, Debebe and Zekarias [63] found that in southern Ethiopia, poverty and income inequality significantly exacerbated household food insecurity, with food-insecure households displaying markedly higher poverty incidence and income inequality levels than food-secure ones. However, other complaints were more common among food-secure households, like access to drinking water, which was reported as an issue by a higher proportion of food-secure households compared to food-insecure households, in both FCS and MAHFP classifications. This counterintuitive finding may stem from higher expectations among food-secure households for reliable and high-quality water sources, while food-insecure households may have normalized limited water access or prioritized other pressing concerns. All households face similar challenges regarding water access—90.8% of the surveyed households collect water from surface ponds, with an average daily collection time exceeding 70 min. Such patterns are consistent with the notion of relative deprivation described in FAO analytical frameworks, whereby households with comparatively better living conditions tend to evaluate their situation against higher expectations and therefore report dissatisfaction even when their objective access conditions are similar to those of their peers. In this sense, complaints may capture perceived gaps rather than absolute deficits, reflecting differences in expectations, aspirations, or reference standards rather than actual inequality [64].

Considering that complaints span multiple domains, these findings reinforce the value of developing a simple multi-sector referral form linking each reported problem to the appropriate service pathway. Such a tool would allow frontline implementers to translate household-level complaints—whether objective or expectation-driven—into clear action routes (e.g., WASH upgrades for water concerns; health referrals for illness; social protection linkages for lack of clothing or bedding; livelihood or VSLA support for poverty-related complaints).

Likewise, although only significant when considering the MAHFP classification, mentioning poverty as a problem of the household was more common in food-secure households, compared with food-insecure ones, which may reflect a heightened awareness and perception of economic challenges among food-secure households, possibly due to their greater exposure to financial responsibilities and aspirations for improved living standards.

Lastly, insufficient farmland was a more frequently reported concern among food-insecure households, aligning with the critical role of arable land in subsistence farming systems, which dominate rural livelihoods throughout the country [65]. These findings also connect to wider debates on land fragmentation and tenure insecurity in Uganda and East Africa. As noted by Bamwesigye et al. [65], more than 90% of Uganda's farm output is produced on plots under five hectares, and customary systems have increasingly undergone subdivision and individualization, constraining both the ability to expand cultivation and the feasibility of adopting long-term investments such as crop rotation or perennial crops. Such fragmentation—combined with insecure or informal land tenure—has been repeatedly linked to stagnant productivity and reduced capacity to cope with shocks. At the regional scale, similar concerns arise under the "East African land rush", where competition for land, boundary disputes and speculative acquisitions can limit smallholders' secure access to cultivable acreage [66], thereby reinforcing the patterns identified in this study. Situating our results within this broader political-economy context helps explain why households reporting insufficient farmland consistently exhibit lower food security: their restricted land base is not only a local constraint, but part of a structural landscape of tightening land availability and insecure tenure across the region.

Determinants of food security status

The regression analyses were restricted to the 157 households that participated in both data-collection phases. Of these, 93 and 50 households were classified as food secure under the FCS and MAHFP indicators, respectively. Considering that the final models retained five and four predictors, the resulting events-per-variable ratios (18.6 and 12.5) exceeded the recommended 10:1 threshold [67], confirming adequate model sizes and stability.

The results of the binary logistic regression model for the FCS indicator are presented in Table 7. The model was developed using the backward elimination method, which began with the introduction of 24 variables and sequentially removed those with the least explanatory power until arriving at the optimal combination that provided the best fit, with 5 variables along with a constant.

Table 7 Logistic regression coefficients (FCS)

Variable	Coefficient (β)	St. error	Sig.	Odds ratio	VIF
Minimum Necessary Household Income	0.276	0.095	0.004	1.318	1.028
Hunger, lack of food	−0.687	0.403	0.089	0.503	1.156
Lack of clothes	−0.819	0.411	0.046	0.441	1.194
Access to drinking water	1.015	0.533	0.057	2.760	1.036
Insufficient farmland	−0.951	0.567	0.094	0.386	1.076
Constant	0.060	0.381	0.875	1.062	

Table 8 Logistic regression coefficients (MAHFP)

Variable	Coefficient (β)	St. Error	Sig.	Odds ratio	VIF
Minimum Necessary Household Income	0.119	0.052	0.021	1.127	1.016
Poverty, money	0.672	0.402	0.094	1.958	1.006
Access to drinking water	1.155	0.442	0.009	3.173	1.013
Insufficient farmland	−1.725	0.797	0.030	0.178	1.022
Constant	−1.754	0.423	0.000	0.173	

The model demonstrates adequate goodness of fit, as indicated by the Hosmer–Lemeshow test (χ^2 = 10.108, $p = 0.258$), with a Nagelkerke R^2 of 0.292 and an overall classification accuracy of 71.6%. The area under the ROC curve (AUC) was 0.762, indicating good discriminatory capacity. The Brier score was 0.192, consistent with moderate predictive accuracy. Calibration plots based on deciles of predicted risk showed good agreement between predicted probabilities and observed proportions of food-secure households, with only minor deviations in mid-probability ranges.

Internal validation was performed through repeated random subsampling (ten iterations with 90/10 splits). The mean AUC obtained (0.745) was close to the full-sample estimate, suggesting limited overfitting and confirming the internal stability of the FCS model. A classification threshold of 0.5 was used.

Among the economic variables analysed, actual household income did not exert sufficient influence to be retained in the model. This contrasts with findings from other studies, such as Asaki et al. [68], who identified a significant relationship between household income and food security. Interestingly, minimum necessary household income was retained in the model (β = 0.276, OR ≈ 1.32, p = 0.004), indicating that each unit increase in perceived necessary income was associated with a 32% increase in the odds of being classified as food secure. This may reflect the added value of subjective estimations in capturing economic pressure more accurately. In rural contexts—where income sources are often informal, irregular, or not fully documented—such perceptions may offer a clearer sense of financial strain. Moreover, what a household considers “necessary” likely encompasses not only material needs but also lived experiences, expectations, and perceived coping capacity—factors that directly influence how food is accessed and managed.

Notably, variables derived from open-ended questions emerged as the most influential predictors in the model. For example, complaints about hunger and lack of food were strongly associated with food insecurity (β = − 0.687, OR ≈ 0.50). Similarly, the variable “lack of clothing” (β = − 0.819, OR ≈ 0.44) showed an even stronger negative association, indicating that households reporting this issue had their odds of being food secure reduced by approximately 56% compared to those who did not express this concern. Complaints about insufficient farmland were associated with a 61% reduction in the odds of food security (OR ≈ 0.39). Interestingly, concerns about lack of access to drinking water were inversely related to food insecurity (β = 1.015, OR ≈ 2.76), showing 2.76 times higher odds of being food secure. This counterintuitive result may reflect higher expectations or awareness among better-off households, rather than actual differences in water access.

Operationally, this distinction matters: if subjective water complaints are interpreted as deprivation without a mechanism to qualify them, better-off households risk being misclassified as vulnerable. A practical solution is the establishment of simple grievance-reporting channels (e.g., SMS or WhatsApp hotlines) through which households can report water-related issues directly to local service providers or implementing partners. Such systems would allow better-off households to demand service improvements without affecting programme targeting, while enabling implementers to distinguish actionable infrastructure gaps from expectation-driven dissatisfaction.

Overall, given the strong predictive performance of a small set of variables, these results could be translated into a simple field scorecard for frontline staff. Each key predictor—minimum necessary income, hunger or lack of food, lack of clothing, insufficient farmland, and dissatisfaction with water access—could be assigned a traffic-light band to guide triage. Households reporting hunger, lack of clothing, or insufficient farmland would fall under a red band, signalling the need for immediate support. Those presenting only one moderate concern could be placed in a yellow band, indicating follow-up or referral. Households without major complaints would fall into a green band for routine monitoring.

For the case of MAHFP, the coefficients for each variable in the binary logistic regression model are presented in Table 8. The model was also developed using the backward elimination method, which began with the introduction of 13 variables and reached the greatest explanatory power with 4 variables. The final model exhibited robustness, as demonstrated by the Hosmer–Lemeshow test (χ^2 = 5.403, $p = 0.714$), a Nagelkerke R^2 of 0.183 and an overall classification accuracy of 72.5%. The area under the ROC curve (AUC) was 0.715, reflecting acceptable discriminatory capacity. The Brier score of 0.188 confirmed adequate calibration, as the calibration plots showed coherent increases in observed food security across deciles of predicted risk, with slightly more variability in mid-range probabilities.

Internal validation through repeated random subsampling (ten iterations with 90/10 splits) produced a mean AUC of 0.687, close to the full-sample estimate and indicating that the MAHFP model also exhibited limited overfitting and satisfactory internal stability. A classification threshold of 0.5 was used.

The final set of predictors in the MAHFP model included Minimum Necessary Household Income, which remained statistically significant ($\beta = 0.119$, OR ≈ 1.13, $p = 0.021$), consistent with the results observed under the FCS classification. As in the previous model, most of the influential predictors were derived from open-ended questions on household challenges, reinforcing the value of integrating qualitative insights into quantitative analysis. Complaints related to poverty or financial difficulties ($\beta = 0.672$, OR ≈ 1.96, $p = 0.094$) and lack of access to drinking water ($\beta = 1.155$, OR ≈ 3.17, $p = 0.009$) were positively associated with food security, indicating that households reporting these issues were more likely to maintain adequate food provisioning throughout the year. In contrast, the complaint about insufficient agricultural land emerged as the strongest negative predictor ($\beta = -1.725$, OR ≈ 0.18, $p = 0.030$). Households reporting this concern had their odds of being food secure reduced by approximately 82%, highlighting once again the critical role of land access in achieving food security. This predictor could serve as a clear trigger for prioritising land-poor households for small-space production packages such as home-garden starter kits, poultry units, or kitchen-garden irrigation sets.

At a broader community level, the MAHFP results also highlight opportunities to strengthen seasonal resilience in villages with systematically low MAHFP scores. Two practical options include (a) introducing seasonal VSLA planning sessions in which groups map expected shortage months and align savings/payout schedules accordingly, and (b) providing training on community or household grain-bank management to reduce lean-season shortages. Such interventions directly address the year-round provisioning deficits captured by the MAHFP indicator and offer implementers a pathway to translate model outputs into concrete programmatic levers.

These seemingly paradoxical results—particularly regarding complaints about poverty or water—may reflect a greater awareness of needs among relatively better-off households, or a higher capacity to articulate problems that, while present, do not compromise their year-round food provisioning. In other words, rather than signalling material deficiency, these perceptions often point to shifting expectations and reference points within the community. Such patterns are consistent with the relative deprivation and aspirational-needs frameworks discussed earlier, whereby households assess their situation not only against absolute conditions but also against evolving expectations and reference groups [64]. In this sense, higher complaint rates among food-secure households may indicate rising aspirations rather than worsening deprivation, with direct implications for livelihoods programming: interventions must account for both material deficits and perceived gaps, recognising that households with better objective outcomes may still express unmet needs that influence their economic decisions, investment priorities, and the kinds of services they seek out.

Despite initially analysing 30 independent variables, only six were retained as significant predictors in the regression models. This limited number may be partly explained by the relative homogeneity of the interviewed population, as well as the strong interdependence among certain household characteristics. Several variables commonly identified in the literature as relevant determinants of food security, such as the cultivation of maize, beans, or plantains [47], did not show sufficient statistical influence to be included in the final models. However, they did show a similar trend to that reported by previous authors, since the cross-tabulations reveal a higher proportion of "food secure" households among those cultivating these crops, suggesting that households growing these crops are generally more food secure than those that do not.

Given the modest sample size ($n = 167$), it is also likely that the statistical power of the models was insufficient to retain additional predictors, particularly for variables with low variability across households. Nonetheless, this limitation reinforces the practical value of focusing routine monitoring on the six predictors that consistently showed the strongest associations across both models, which together offer a concise and operationally feasible set of indicators for frontline implementers.

A notable feature of this study is that most of the predictive variables retained in the models originated from open-ended questions. While this reduces the comparability of the results with studies based on more standardized survey instruments, it also underscores the importance of incorporating qualitative dimensions into quantitative analysis. Allowing respondents to express their own concerns provides valuable insights into the contextual realities shaping food security. In this sense, evidence from participatory scenario initiatives in East Africa demonstrates that bringing together participants' experiential insights and formal analytical methods can significantly improve the legitimacy and applied relevance of research for policy and programming [69].

That said, the findings still align with key conclusions from existing literature. For example, Hashmiu et al. [51] emphasized the importance of land ownership in improving household food security through greater access to income and food crops. At a broader scale, large-scale land acquisitions across Sub-Saharan Africa, which may restrict access to farmland for local communities, have been associated with reduced cereal availability and increased malnutrition, despite being framed as development opportunities [70]. In line with these trends, households in the present study that reported insufficient agricultural land consistently exhibited lower levels of food security. These results resonate with broader debates on the East African "land rush", as discussed earlier. Empirical evidence shows that large-scale land acquisitions across Sub-Saharan Africa have often constrained local food systems by reducing domestic staple food production and increasing malnutrition, particularly when acquired land is diverted from smallholder use toward export-oriented crops [70]. As highlighted by Kinda et al., these dynamics tend to undermine food security in contexts where rural households already depend heavily on small plots for subsistence. The perceptions captured in our study—especially the consistent reporting of insufficient farmland among food-insecure households—mirror these structural pressures, suggesting that limited access to cultivable land in rural Uganda is not only a household constraint but part of a wider regional pattern linked to competition over land and changing land governance.

Similarly, Shamah-Levy et al. [71] highlights the negative impact of inadequate access to drinking water on food security. Although the objective variable "main source of drinking water" was not statistically significant in our models, self-reported complaints about water access showed a significant, albeit inverse, relationship with food security. Households that expressed dissatisfaction with water availability tended to have higher levels of food security, suggesting that better-off households may hold higher expectations regarding their living conditions. In any case, Uganda-based studies reinforce the close interdependence between water access and household food security. For example, Bamwesigye et al. [65] highlight that unreliable or distant water sources limit households' capacity to cook diverse foods, maintain hygiene, and allocate labour to agricultural production—three pathways directly affecting food utilisation and, ultimately, food security. These findings reflect national concerns about water scarcity and the heavy labour burden associated with water collection, suggesting that even when complaints stem from higher expectations among better-off households, the structural link between WASH conditions and food security remains evident.

Other variables, such as membership in farmer groups or cooperatives, which have been identified as highly influential by authors like Nkomoki et al. [34], were underrepresented in our sample and had to be excluded during the initial stages of this study, representing a clear data gap that future research should address.

Finally, the variable "household size" showed a trend contrary to what is commonly reported. While many studies (e.g. [19, 32, 50], associate larger households with greater food insecurity, our findings indicate the opposite: food secure households had, on average, more members (7.89) than food-insecure ones (6.73). This may reflect a greater availability of labor, income diversification, or economies of scale in larger households, though further research would be needed to explore this relationship in depth. Evidence from other East African settings also supports this interpretation. In Ethiopia, for instance, several authors have reported that larger households tend to achieve better food security outcomes due to greater labour availability and the benefits of pooled resources [53, 54].

Conclusion and policy implications

This study identifies a small set of consistently influential determinants of household food security in rural Sembabule District, Uganda—namely access to cultivable land, perceived minimum necessary income, water availability, and self-reported deprivation indicators. These findings underline the importance of combining standardized measures (FCS and MAHFP) with perception-based variables to capture the multidimensional and seasonal nature of food insecurity.

Based on the evidence, five policy priorities clearly emerge, each aligning with Uganda's National Development Plan III (NDP III):

- Strengthen access to land for cultivation. Insufficient farmland was one of the strongest negative predictors in both models. Expanding secure access to arable land—particularly under customary tenure—would enhance food availability, diversification, and income generation. Targeted support for land-poor households, including small-space production packages and home-garden models, could mitigate structural constraints and increase resilience. This priority directly supports the objectives of the NDP III's Agro-Industrialisation Programme.
- Improve financial literacy and household resource management. Perceived minimum necessary income, rather than actual income, had a stronger predictive effect on food security. This suggests that

interventions should strengthen households' capacity to plan expenditures, manage irregular cash flows, and stabilise consumption. Locally tailored financial literacy modules delivered through VSLAs or community-based training could substantially reduce vulnerability. Such measures align closely with the Community Mobilisation and Mindset Change Programme under NDP III.

- Invest in rural water infrastructure and reduce time-to-source burdens Despite higher dissatisfaction among food-secure households, nearly all respondents relied on unsafe surface ponds and spent over an hour daily collecting water. Improved protected water points, storage systems, and household-level WASH upgrades would strengthen the utilisation dimension of food security and reduce labour constraints, particularly for women. These investments correspond directly to the Water, Sanitation and Hygiene (WASH) priorities set out in NDP III.
- Expand women-centred agricultural extension Given that 98% of respondents were women, gender-responsive extension services are critical. Training on integrated crop–livestock systems, home-gardening, and food preparation can support adoption of resilient practices and enhance household nutrition outcomes. This recommendation advances the goals of NDP III's Human Capital Development Programme.
- Integrate mixed-indicator monitoring systems The weak agreement between FCS and MAHFP confirms that single indicators may mask seasonal deficits. Routine monitoring should therefore combine both metrics to distinguish short-term consumption deficits from longer-term provisioning gaps. Strengthening such monitoring systems is consistent with the Governance and Statistics agenda within NDP III.

Future research directions

To support national strategies, future studies should analyse land fragmentation dynamics, investigate labour-sharing mechanisms within large households, document food-for-labour arrangements (a clear gap identified here), and test seasonal VSLA planning or grain-bank models in low-MAHFP villages.

Abbreviations

ANOVA Analysis of Variance
ASALs Arid and Semi-Arid Lands
FANTA Food and Nutrition Technical Assistance
FAO Food and Agriculture Organisation
FCS Food Consumption Score
HDDS Household Dietary Diversity Score
HHS Household Hunger Scale
MAHFP Months of Adequate Household Food Provisioning
NDP III Uganda's National Development Plan III
NGO Non-Governmental Organization
OR Odds Ratio
UBOS Uganda Bureau of Statistics
UGX Ugandan Shillings
VSLAs Village Savings and Loan Associations
WASH Water, Sanitation and Hygiene
WDDS Women's Dietary Diversity Score
WFP World Food Programme

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Author contributions

All authors contributed to the conceptualization of the study. JS conducted the fieldwork and interviews with participants, supported by the social worker from Kukorra Hamu Uganda. JS and RP were responsible for data curation. JS, LM, and RA participated in the formal analysis of the results. JS wrote the original draft of the manuscript, while LM and RA contributed to its review and editing. All authors read and approved the final manuscript.

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Data availability

Due to the sensitive nature of the questions asked in this study, respondents were assured that their raw data would remain confidential and not be shared. As a result, the datasets generated and analysed during the current study are not publicly available but may be shared in anonymized form by the corresponding author upon reasonable request.

Declarations

Ethics approval and consent to participate

Ethical approval for this research was granted by the *Oficina de Investigación Responsable (OIR)* at the Universidad Miguel Hernández de Elche [Reference number: DEA.LMM.02.22]. All participants provided informed consent before the interviews.

Competing interests

The authors declare no competing interests.

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